Project acronym:	BYTE
Project title:	Big data roadmap and cross-disciplinarY community for addressing socieTal Externalities
Grant number:	285593
Programme:	Seventh Framework Programme for ICT
Objective:	ICT-2013.4.2 Scalable data analytics
Contract type:	Co-ordination and Support Action
Start date of project:	01 March 2014
Duration:	36 months
Website:	www.byte-project.eu

Deliverable D3.2:
Case study reports on positive and negative externalities

Author(s):	Guillermo Vega-Gorgojo (UiO), Anna Donovan (TRI), Rachel Finn (TRI), Lorenzo Bigagli (CNR), Sebnem Rusitschka (Siemens AG), Thomas Mestl (DNV GL), Paolo Mazzetti (CNR), Roar Fjellheim (UiO), Grunde Løvoll (DNV GL), EarthObvsrge Psarros (DNV GL), Ovidiu Drugan (DNV GL), Kush Wadhwa (TRI)

Dissemination level:	Public
Deliverable type:	Final
Version:	1.0
Submission date:	5 June 2015

Table of contents

EXECUTIVE SUMMARY

This deliverable presents the case study reports on positive and negative externalities in the use of big data that we have undertaken in the BYTE project. The case studies correspond to the domains of crisis informatics, culture, energy, environment, healthcare, maritime transportation and smart cities. Following the methodology reported in deliverable D3.1, we have gathered evidence from the case studies by means of semi-structured interviews, disciplinary focus groups and literature review. Overall, we have conducted 49 interviews with data experts from each case study discipline and we have counted with 6-12 external domain experts per focus group.

The crisis informatics case study is focused on the use of social media – especially Twitter data – to support humanitarian relief efforts during crisis situations. The case shows how the use of big (and open) data can provide significant gains and benefits in terms of the provision of humanitarian aid, including better, more targeted and more resource efficient services. However, issues related to privacy, data protection and resource drains remain significant.

The culture case study examines a pan-European public initiative that provides open access to digitised copies of cultural heritage works. Although there is some debate as to whether cultural data is in fact big data, this discussion evolves as the volume, velocity and variety of data being examined shifts. The variety challenge is especially relevant in this case, given the different types of cultural objects and associated metadata. Moreover, the diversity of stakeholders and their complex interrelations produce a number of positive and negative impacts for society, as well as prominent challenges faced by such initiatives. Some of these challenges include potential and perceived threats to intellectual property rights and the establishment of licensing schemes to support open data for the creation of social and cultural value.

The energy case study analyses the impact of big data in exploration and production of oil & gas in the Norwegian Continental Shelf. This is a data intensive industry that is shifting from mere data storage to more proactive uses of data, especially in the operations area. Our investigation reveals significant economical impacts – especially through data analytics, open data and commercial partnerships around data – although there are concerns with existing business models and reluctance of sharing data by oil companies. Big data can also be applied to diminish safety and environment concerns, while personal privacy is not problematic in this domain. However, cyber-threats are becoming a serious concern and there are trust issues with the data. In the legal side, regulation of data needs further clarification and ownership of data will become more contract-regulated.

The environment case study is probably the most mature in terms of big data. Stakeholders take for granted the availability of data, especially from authoritative sources such as prominent earth and space observation portals, and there is a growing interest in crowd-sourced data. Europe is leading this area and there is a general perception that the technical challenges can be easily overcome, but policy-related issues and data quality are the main barriers. Given the myriad of applications of environment data, there are many opportunities for economic growth and better governance of environment challenges – although there are also negative externalities, such as the possibility of putting the private sector to a competitive advantage. Data-intensive applications may increase awareness and participation; however, big-brother-effect and manipulation, real or perceived, can be problematic. With respect to legal externalities, regulation needs clarification, e.g. on IPR. Finally, political externalities include

the risk of depending on external sources, particularly big players, as well as EarthObvspolitical tensions.

The healthcare case study is conducted within a health institute at a medical university in the UK. This institute facilitates the discovery of new genes, the identification of disease and innovation in health care utilising genetic data. The data samples used, analysed and stored can easily reach a significant volume, especially when aggregated with other genetic samples or with other health dataset. The sequencing of these samples is computer-intensive and requires big data technologies and practices to aid these processes. The aggregation of health data extends the potential reach of the externalities produced by the utilisation of health data in such initiatives. For example, research with these samples can lead to improved diagnostic testing and treatment of rare genetic disorders and assist in administering genetic counselling. Utilisation of genetic data also highlights when more controversial impacts can arise, such as in the case of ethical considerations relating to privacy and consent, and legal issues of data protection and data security for sensitive personal data.

The maritime transportation case study analyses the use of big data in the shipping industry that accounts more than 90% of global trade. Despite its importance, the case study strongly indicates that major parts of the maritime transport sector are in a very early stage for adoption of big data, since ship owners and other stakeholders do not perceive the value of data. Moreover, a common denominator in this industry is the unwillingness to share any raw data, and if they have to, this is only done on an aggregated level.

Finally, the smart cities case study examines the creation of value from potentially massive amounts of urban data that emerges through the digitalized interaction of a city's users with the urban infrastructure of resources. The state of big data utilisation in digitalising cities can be summarized as developing, with some cities currently building the necessary big data structures, be it platforms or new organizational responsibilities. With respect to the societal externalities of big data in the smart cities domain, the economies of data favour monopolistic structures, which may pose a threat to the many SMEs in cities and the small and medium cities. However, open source, open platforms, and open data have the potential to level the playing field and even spur more creativity and innovation. While big data in smart cities has many possibilities for social good, there are a number of negative externalities that need to be addressed, such as the strong reliance on data-driven services.

CRISIS CASE STUDY REPORT – *INNOVATIONS IN SOCIAL MEDIA ANALYSIS, HUMAN COMPUTING AND ARTIFICIAL INTELLIGENCE*

SUMMARY OF THE CASE STUDY

This case study examines the use of social media data, especially, but not exclusively to assist in humanitarian relief efforts during crisis situations. The case study focuses on the Research Institute for Crisis Computing and their work using Twitter data to "map" crises for humanitarian organisations. This case study raises a number of interesting issues related to big data uses, technological challenges and societal externalities. The analysis and conclusions demonstrate that the use of big data in this context provides significant gains and benefits in terms of the provision of humanitarian aid, including better, more targeted and more resource efficient services. However, issues related to privacy, data protection and resource drains remain significant.

1 OVERVIEW

The case study in crisis informatics examines the use of big data during crisis situations, which is an emerging area of big data practice. Crisis informatics is an umbrella term that "includes empirical study as well as socially and behaviourally conscious ICT development and deployment. Both research and development of ICT for crisis situations need to work from a united perspective of the information, disaster, and technical sciences".[1] Furthermore, while the case study will focus primarily on political crises and natural disasters, it is important to note that crisis informatics links with a number of activity areas including humanitarianism, emergency management, first response and socio-economic development. Furthermore, while this case study focuses on the use of big data in responding to crises, crisis informatics is also implicated in relation to all three phases of crisis management: preparedness (training, baseline information gathering, simulations, conflict prevention), response (coordination, information gathering, provision of humanitarian relief or aid) and recovery (resource allocation, population monitoring, development).[2]

This case study focuses on crisis mapping and the combination of machine intelligence and human intelligence to mine social media and other data sources to create crisis maps. A specialist research institute, pseudonymised as Research Institute for Crisis Computing (RICC), sits at the centre of this case study, and has provided access to key staff members internal to the institute and additional contacts in international humanitarian and governance organisations to assess the impact of the systems they are developing. RICC runs two projects, both of which focus on meeting humanitarian needs with a combination of "human computing and machine computing" (artificial intelligence) (Director, RICC – I-RICC-D). Project 1 uses a combination of crowd sourcing and AI to automatically classify millions of tweets and text messages per hour during crisis situations. These tweets could be about issues related to shelter, food,

[1] Palen, L., S. Vieweg, J. Sutton, S.B. Liu & A. Hughes, "Crisis Informatics: Studying Crisis in a Networked World", *Third International Conference on e-Social Science*, Ann Arbor, Michigan, October 7-9, 2007.
[2] Akerkar, Rajendra, Guillermo Vega-Gorgojo, Grunde Løvoll, Stephane Grumbach, Aurelien Faravelon, Rachel Finn, Kush Wadhwa, and Anna Donovan, Lorenzo Bigagli, Understanding and Mapping Big Data, BYTE Deliverable 1.1, 31 March 2015. http://byte-project.eu/wp-content/uploads/2015/04/BYTE-D1.1-FINAL-compressed.pdf

damage, etc., and this information is used to identify areas where response activities should be targeted. Project 2 examines multi-media and the photos and messages in social media feeds to identify damage to infrastructure. This is a particularly important project as the use of satellite imagery to identify infrastructure damage is only 30-40% accurate and there is a generalised difficulty surrounding extracting meaningful data from this source (Director, RICC). The project uses tens of thousands of volunteers who collect imagery and use social media to disseminate it. These activities link with high volume, high velocity data and introduce a significant element related to veracity. Specifically, the combination of crowd sourcing and AI are used to evaluate the veracity of user-generated content in both these projects. In each project, human computing resources are used to score the relevance of the tweets in real time, which is used as a basis for the machine-learning element. These volunteers are recruited from a pool of digital humanitarian volunteers, who are part of the humanitarian community.

The projects use crisis response as an opportunity to develop free and open source computing services. They specifically create prototypes that can be accessed and used by crisis response organisations for their own activities. The prototypes are based on research questions or problems communicated to the centre directly from crisis response organisations themselves. As such, they ensure that the output is directly relevant to their needs. However, this does not preclude other types of organisations from accessing, re-working and using the software for a range of different purposes. The case study has enabled BYTE to examine a specific use of big data in a developing area, and to examine positive and negative societal effects of big data practice, including: economic externalities, social and ethical externalities, legal externalities and political externalities.

1.1 STAKEHOLDERS, INTERVIEWEES AND OTHER INFORMATION SOURCES

In order to examine these issues effectively, the case study utilised a multi-dimensional research methodology that included documentary analysis, interviews and focus group discussions. The documentary analysis portion of the work included a review of grey literature, mass media and Internet resources, as well as resources provided by the Research Institute for Crisis Computing about their activities. It also examines specific policy documents related to the use of data by international humanitarian organisations, such as the International Red Cross Red Crescent Society's updated *Professional Standards for Protection Work,* which includes a section devoted to the protection of personal data.[3]

The Research Institute for Crisis Computing works with a number of different organisations to use data to respond in crisis situations. As a result, this case study has conducted interviews with four representatives from RICC and three representatives from RICC clients, including the humanitarian office of an international governmental organisation (IGO) and an international humanitarian organisation (IHO). Both clients have utilised RICC software and mapping services in their crisis response work. Table 1provides information on the organisations, their industry sector, technology adoption stage, position on the data value chain as well as the impact of IT on crisis informatics within their organisation.

[3] International Red Cross Red Crescent Society, *Professional Standards for Protection Work*, 2013. https://www.icrc.org/eng/assets/files/other/icrc-002-0999.pdf

Table 1: Organizations examined

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
RICC	Computer science	Early adopter	Acquisition Analysis Usage	Strategic role
International governmental organisation	Humanitarian organisation	Early majority	Usage	Support role
International humanitarian organisation	Humanitarian organisation	Early majority	Usage	Support role

The case study interviewed high-level decision makers in each of these organisations, and in the case of RICC, researchers also interviewed scientists and senior scientists who were directly involved in the design and development of the systems utilised. Table 2 provides information about each of the interview participants, using the classification system described in the BYTE *Stakeholder Taxonomy*[4] to indicate their knowledge about big data, their position with respect to big data advocacy and their level of interest in using data for novel purposes.

Table 2: Profiles of interview participants

Interviewee	Organization	Designation	Knowledge	Position	Interest
I-RICC-S	RICC	Scientist	Very high	Supporter	Very high
I- RICC-SS	RICC	Senior scientist	Very high	Supporter	Very high
I-RICC-D	RICC	Director	Very high	Supporter / advocate	Very high
I-RICC-PM	RICC	Programme manager	Very high	Supporter	Very high
I-IHO-HP	International humanitarian organisation	Head of project	High	Moderate supporter	High
I-IHO-HU	International humanitarian organisation	Head of unit	High	Moderate supporter	High
I-IGO-PO	International governmental organisation	Programme officer	Very high	Supporter / advocate	Very high

Each of these interview participants was situated at the developed end in terms of their knowledge about, interest in and support for the use of big data in crisis informatics. In particular, members of the RICC consistently described themselves as "thought leaders" in this area and the space that they are working in as "green fields". This indicates where they see themselves on the scale of technology deployment. Interviewees from the international humanitarian organization were situated as slightly less knowledgeable, interested in and supportive of big data, but this slight difference was primarily related to the fact that their work still largely relied upon paper records and direct observations. This was particularly the case with respect to long-term crises such as political crises, as their work was equally focused on long-term events as well as acute events.

[4] Curry, Edward, Andre Freitas, Guillermo Vega-Gorgojo) Lorenzo Bigagli, Grunde Løvoll and Rachel Finn, *Stakeholder Taxonomy*, BYTE Deliverable 8.1, 2 April 2015. http://byte-project.eu/wp-content/uploads/2015/04/D8.1_V1.2.pdf

In addition to the anonymised interviews, data was also collected in a focus group with crisis informatics experts from the following organisations and stakeholder categories. Table 3 lists the organisations and stakeholder categories to which each focus group participant belonged.

Table 3: Focus group participants

Participants	Description
VU University of Amsterdam, NL	Academic
Antwerp Fire Service, BE	End-user
UK All Party Parliamentary Committee on Drones, UK	Government
Treelogic, ES	Industry
Sheffield Hallam University, UK	Academic
Oxford Computer Consultants, UK	Industry
Civil Protection and Emergency Number Agency, ES (Catalan Government)	End-user
Big Brother Watch, UK	CSO
Group on Earth Observations Secretariat, CH	Data centre
University of Patras, EL	Academic
Veiligheidsregio Twente, NL	End-user
Ministry of Interior, EL	Government

To conform to established ethical practice in the conduct of research, all of the quotes from focus group participants are anonymised by stakeholder category.

1.2 ILLUSTRATIVE USER STORIES

So to summarise the international government organisation asked us to tell them where infrastructure was most damaged. And so RICC, using the artificial intelligence tool, we looked for classifiers, which is what the tool does. It searches at a big data level, does the analytics and then spits out that piece of data into another tool, which maps the information. The mapping is where the community collaboration comes in, to make quick small bite size decisions like one-minute, two-minute task nothing like two-hour tasks. And then all of that becomes aggregated and rolled up into a datasets that people can analyse and say where is the infrastructure damage the most. And so they verify the reports and so we provided the international government organisation with a map that showed them where the critical points were. And while they had their own insights, having done some site visits and having been on the ground, we were able to add a layer of data from citizen data, from the tweets to be able to kind of inform their decisions. […] Now originally some of the reports were about how people…you know how did it affect them in terms of food and not finding water, but the longer term plans when people in the international government organisation take that information they can strategically plan for which region had been most hit. And they can move their resources in that way. We are not moving the resources of a specific area, [but] we can help informed decision makers based on what we've seen and what real citizens have said. (Programme manager, RICC – I-RICC-PM)

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

2.1 DATA SOURCES

There are a range of data types that are relevant for crisis informatics, especially given the broader focus on humanitarian relief, development and crisis response. In order to produce the crisis maps that are useful for humanitarian, relief and response organisations, RICC primarily uses social media data from Twitter and information from text messages (i.e., direct

communication to agencies). These information sources can include text as well as still and moving images. In addition, they may also collect information from news media and they are exploring integrating aerial imagery and satellite imagery into their data processes. The tweets can number up to "a couple of hundred messages per minute" and "a few hundred thousand per day" (Senior scientist, RICC – I-RICC-SS). More broadly, the international government and humanitarian organisations work with data such as global information systems data, data on administrative boundaries in particular countries, mapping information on roads, rivers, elevation and other EarthObvsgraphic characteristics, public health as well as detention (of political dissidents) and their sentences. These data records can number up to three million records including structured and unstructured data, which can be challenging to analyse with machines. However, although not specifically used by the case study organisation, other data types may also be useful for crisis informatics, including sensor data from buildings, roads and other infrastructure, GIS data, seismic data, weather data and satellite image data, image data from drones and others.

Across these different organisations, data may be collected automatically or it may be collected by hand using manual records. The RICC collects data automatically, by sampling directly from Twitter and by utilising information embedded within the Tweet, specifically location data, and increasingly visual and image data. This data is born digital, and thus it is relatively straightforward to collect samples automatically. Furthermore, while individuals do not necessarily know that their data is being collected and analysed by RICC, some data characteristics are controlled by the user. For example, the inclusion of location information in tweets is something that "you have to opt into" (Senior scientist, RICC, I-RICC-SS). Significantly, individuals, independent of RICC, produce this social media data and RICC are taking advantage of this existing data set. With respect to international humanitarian organisation data, data is primarily collected "directly from individual people as well as indirectly through information from hospitals and other organisations" (Head of unit, IHO, I-IHO-HU). The IHO then seeks to "triangulate the information with other sources of information. So it maybe the press, it maybe the authorities, social media whatever is available a complete view as possible." (Head of project, IHO) Unlike RICC, the IHO data is collected from individuals in a targeted manner, thus it is "pulled" by the IHO rather than being "pushed" by people themselves.

2.2 DATA USES

The RICC is committed to using this data analytics tool for crisis management, humanitarian relief and development, all within the general field of crisis informatics, as well as other social causes. Within the crisis mapping work, data is primarily used to "augment situational awareness to inform decision making" for the clients (Director, RICC). Representatives from both the IGO and the IHO concur with this assessment, adding an element of predictive analytics as well. For example, the Programme Officer for the IGO stated that the tool "helps kick-start things in the early days of an emergency" and allows relief workers to get an understanding of the situation, especially in "remote locations where we can get pictures that we haven't heard anything about". Speed is a key improvement here, where prior to the mapping tool, it would have taken the IGO days to gather information. In addition, the RICC are interested in integrating automated processing of images into their service. As the Director notes, "We now have access to satellite imaging and so what we want to do is bring that sort of human computing/machine computing hybrid to imagery analysis as well as pictures taken on Smart phones."

The IHO also noted the importance of having better information more quickly to assist in decision-making. However, the IHO also noted that this information also helps them by providing "early warnings". This could include "trend analysis" and "predicting which populations are vulnerable" to health risks, abuse or other additional effects (Head of Unit, IHO). For example, having a greater understanding of population movements or population displacement can impact future planning and risk assessment:

> [There is a tool] called FlowMiner which is trying to use let us say anonymised cellular data to track population displacement. So they were able after Haiti to show they could have predicted [displacement] using cell data very quickly. They could know where numbers of people went and my understanding was that it actually took several weeks for the larger [IGO] related assessment to determine effectively the same thing. And then there are also other groups looking at it from a predictive standpoint, where are people usually going on holidays. So in a Christian country, where are they going for Easter or where are they going for Christmas. And then say there's a major crisis in Port Au Prince or in Kathmandu where would people be most likely to go and then prepare measures in those directions. (Programme Officer, IGO)

Again, while the speed of data availability is important in this example, the predictive element and the ability to use predictive analytics to prepare for a crisis as well as respond to one demonstrates that big data can stretch across different phases of a crisis.

Importantly, the artificial intelligence tool itself is application neutral (in the sense that the analysis of the Twitter data can be applied to any application – e.g., brands, sports teams, etc.), but the RICC team have committed to using it for crisis management and other social causes, including environmental protection, health, local community improvement, youth engagement, traffic management and election monitoring.

2.3 DATA FLOWS

While the application of the artificial intelligence tool to some of these other social causes might result in a more local data processing, the data from the crisis management and response applications result in an international flow of data. Specifically, data from social media are "pushed" by those affected by crises and disasters to the Internet, which is itself international. However, the further processing of this data also integrates a global network of analysis. First, a network of digital volunteers, located anywhere in the world, analyzes data from specific Tweets or sets of Tweets. The data from this first processing is then fed to the artificial intelligence tool currently hosted by the RICC in a small developing country. The data from this secondary processing is then fed to large, international humanitarian and relief organizations in cities such as Geneva, London or New York as well as others, who use it to provide aid and relief in the country where the social media information originated. Thus, the data itself makes a global journey in order to be utilized "on the ground" in each local context.

2.4 MAIN TECHNICAL CHALLENGES

As noted in in the Stakeholder taxonomy,[5] the big data value chain consists of the following steps: Data acquisition, analysis, curation, storage and usage. In crisis informatics, technical challenges were reported in all of these areas. However, the challenges associated with data analytics and data curation appeared to be most immediate to stakeholders in the interviews and the focus groups.

[5] Edward Curry. "Stakeholder Taxonomy". BYTE Project. Deliverable 8.1. 2014.

With respect to **data acquisition**, acquiring proprietary data, acquiring a full data set, and acquiring valid data were reported as key issues. For example, an academic expert from the focus group noted that information needs differ at different levels of an organisation. Satellite and scientific data is more useful at higher levels of an organisation for planning and resource allocation, but this additional information is not necessarily useful for responders. In contrast, responders need immediate and current information to react to incidents as they occur. Twitter has emerged as a key information resource for these immediate responders for two reasons, first because it is up-to-date and second because it is publicly available. Thus, there is no issue with respect to being able to access the data. In fact, the Director of RICC described Twitter data as a "lower hanging fruit in terms of data access". However, even with this publicly available information, RICC still works with a sample of Twitter data, albeit a large sample. According to one of the RICC scientists, nobody "gets access to the full stream Twitter samples, it is just the way it is" (I-RICC-S). In fact, the RICC have had to negotiate with Twitter to enable them to use the sheer amount of data that they process. Specifically, RICC "have triggered a few alarms" with Twitter, who have contacted RICC to enquire about their activities (Senior scientist, RICC – I-RICC-SS). However, according to the RICC, Twitter does allow such usages in particular circumstances, including humanitarian purposes. Nevertheless, working with an incomplete data set always raises risks that the data that is analysed can be misinterpreted. As a focus group end-user noted, "you don't know what you haven't picked up".

However, the RICC and other organizations would like to be able to access information from other social media sources as well as other sources, and accessing these closed data sets is a challenge that must be met in order to ensure as full and representative a data set as possible. In addition, an end user from the focus groups reported that when dealing with crises involving private property, the owner of the private property is the owner of the data. This can make preparatory activities difficult since the data is not accessible when there is no incident. Finally, ensuring that data is up-to-date is also a significant technical challenge, as "outdated information is essentially misinformation" (End user, focus group). Yet, although these challenges were discussed, interview and focus group participants did not necessarily prioritized these.

In contrast, challenges related to **data analysis** provoked significantly more discussion in interviews and focus groups. The RICC interview participants all prioritized software development challenges in their discussion of technical challenges, which reflects their primary focus on software development for crisis situations. These challenges were primarily related to fixing bugs and working with a system that was still under development. As the RICC Director notes, "Because we are a computing research institute, I think our first responsibility is to make sure that we evaluate the robustness of our tools, of our technologies. Is it actually performing as it's supposed to perform? Are there bugs? Is it crashing?" (I-RICC-D) Furthermore, the RICC uses a software development methodology that they describe as "agile development", where they deploy the software during crises and emergencies in order to identify those bugs, because "we learn more during 24 hours of a real world deployment on everything that is not right with our platform than we do in three months when they are no disasters" (Director, RICC – I-RICC-D). Yet, the use of an immature system requires some expectation management on the part of the clients. The RICC ask them to certify that they understand they are working with a system that is under development, that has not been fully tested and which may not produce any added value. Nevertheless, according to the RICC, their clients agree to deploy the system because they do get added value from it and they recognise the value in testing the system in an operational environment.

Outside of the RICC, the IGO and focus group participants reported that **standardization** at the analytic and policy level represented a challenge with respect to data analysis. An end user from the focus group noted that during a crisis, data are being collected in different formats and it is nearly impossible to analyse all of the data available in time-sensitive situations because of these different formats. Yet, the Programme Officer from the IGO was more focused on standardization at the policy level. He argued that he would welcome more standardization in terms of hash tags on Twitter, which would significantly improve data capture and detailed analysis. He argued that this initiative could be led by national and local governments and responding agencies.

Data curation was a key issue for the RICC, who use a corps of **digital volunteers** to help curate data coming in from Twitter. Specifically, the RICC use a combination of human computing and machine computing, which takes the data through multiple layers of processing. The population of tweets collected by the RICC are sampled and then distributed to a large network of "digital volunteers" who label the Tweets and then score them for relevance. This sampling does two things. First it enables the processing of the data to begin quickly, using up to tens of thousands of volunteers to undertake the initial analysis. Second, it provides the machine-learning component with a set of data to learn from, in order to automatically process the full data set held by the RICC. As such, the sample tweets initially labelled and analysed by humans, are then turned over to the artificial intelligence software:

> The machine can then take those tweets that are all labelled with infrastructure damage and process them and start to "learn" what that infrastructure damage tweet looks like based on human-labelled data. The machine learns and learns and learns it is continually fed more and more batches of one hundred…sets of one hundred tweets that are labelled with this particular category of information. Eventually the machine gets better and better at recognising this particular type of information in the tweet and can do it more quickly and can do it automatically. (Scientist, RICC – I-RICC-S)

This solution to data curation may be applicable to other contexts and uses of big data; however, the recruitment of such volunteers also raises social and ethical issues, as discussed in more detail in Section 3.2.

RICC and focus group participants also agreed that **data storage** was a key technical challenge. The RICC reported:

> [W]hat we need is servers, much better bigger servers, […] we need basically some serious access to Amazon web services to be able to scale the deployment of the platforms and to do all the work we need. You know if we get to a point where we deploy [the tool] and we get more than ten thousand volunteers that show up that platform would crash. And that is not a good thing for anyone (Director, RICC)

Focus group participants also concluded that **cloud solutions** were a primary need and that public-private partnerships could be forged to host crisis informatics services. While the RICC is actively soliciting such partnerships, these also introduce their own potential challenges and impacts, as will be discussed in more detail in Section 3.4 below.

Finally, research participants also reported challenges in the usage of data in crisis informatics, where data usage here refers to the use of data by clients such as humanitarian organizations, response organizations and governmental organizations. Primarily, there were reported

challenges around **organizational culture** that made it difficult to integrate these services into existing workflows and decision-making mechanisms. The Programme Officer from the IGO stressed the importance of using existing mechanisms to translate the new information provided by big data:

> People saw the online crisis map and they said okay that is just a bunch of red dots, it is too hard to drill in everything. But I had people take the data and take certain parts of the data and create the regular [IGO] info graphics.
>
> *Right, so it became something that was familiar to them.*
>
> Exactly. So this is what I keep stressing with my information management officer. Don't create new products out of this augment what you already have (Programme Officer, IGO, I-IGO-PO)

While the Programme Officer's activities represent an important possible solution to this issue, it also required additional data processing work that would need to be undertaken by the RICC (or other tool providers) or the client. In the former case, this would require access to those existing mechanisms, and in the latter case, it would require data analytic skills. In either case, it requires a significant amount of preparatory work and additional resources, which may not be prioritized outside of a crisis situation.

2.5 BIG DATA ASSESSMENT

Interview and focus group participants in the crisis informatics case study were not particularly invested in "big data" as a descriptor for the activities in which they were engaging. However, their descriptions of their work did reference many of the crisis points reflected in the "big data" definition, including especially volume, velocity and variety. Almost all of the interview participants indicated a preference not to use the term "big data", preferring instead to talk about the challenges they were addressing. For example, the RICC senior scientist argued that the important factor for him is whether the data "requires computers to be analysed", similarly the Programme Manager discussed challenges related to the number of research questions being analysed by a particular data set, while the Director described the main challenges as "filter failure". However, as noted above, the RICC is dealing with hundreds of thousands of data points, which represents a significant volume. The IHO is also working with approximately 100,000 data points, but for them the primary challenge is around the complexity of the data, particularly as much of the data is unstructured. Similarly, one of the end users from the focus group argued that his primary challenges were variety and velocity. Specifically, as already noted above, complex data coming from different systems in different formats needs to be analysed quickly in order to be actionable by responders on the ground. Finally, veracity also emerged as a data issue, which was a key innovation offered by RICC through the combination of human computing to verify and score the information and automated, machine computing to further process it and learn from these verified information sources.

Summary

The analysis of the data being used in the crisis informatics sector, the processing activities and the challenges give a broad overview of the relative maturity of the use of big data in this sector. This analysis reveals that crisis informatics is in the early stages of integrating big data into standard operations and the key improvement is that the analysis of this data improves situational awareness more quickly after an event has occurred. However, there are significant

challenges around access to proprietary data sets and the ability to integrate diverse information, especially image data. Second, the crisis informatics case sector, in general, is primarily focused on a specific type of social media and EarthObvsgraphical data for mapping purposes. While this is obvious given the specific case study chosen, this focus was also reflected in the literature review and focus groups and represented a key finding upon which focus group participants were asked to comment. Based on all the data sources, there has not yet been much progress integrating other data types – e.g., environmental measurements, meteorological data, etc. Third, a key innovation in this area, not yet well reflected in other sectors is the use of human computing, primarily through digital volunteers, to curate the data by validating it and determining how trustworthy it is. However, a key message from the data was that while these tools represent important innovations and improvements in crisis informatics, big data tools should not be "oversold" (Programme Officer, IGO, I-IGO-PO) and technological tools should not replace pen and paper or gut feelings (End user, focus group). These cautions are particularly important given that while these uses of big data enable clear benefits (i.e., positive externalities) they also raise potential negative externalities, each with respect to economics, social and ethical issues, legal issues and politics that are analysed in Section 3.

3 ANALYSIS OF SOCIETAL EXTERNALITIES

The primary contribution of the BYTE project is the examination of the impacts of these uses of big data on third-party stakeholders and society in general. As such, BYTE is examining the economic, social and ethical, legal and political issues that are generated by these big data practices. The purpose of this activity is to identify positive externalities, or impacts, that the big data sector should try and augment or expand, as well as negative externalities that the sector should try to mitigate or address. This section examines the positive and negative externalities in each of these categories, based on the list of externalities included in Appendix A (see Table 55).

3.1 ECONOMICAL EXTERNALITIES

The use of big data in the crisis informatics environment is associated with a number of positive and negative economic externalities, where economic externalities also include the potential for innovation. Once of the principal areas of positive economic externalities is through the creation of new business models, including social considerations as well as economic ones. This means that the business model is not only focused on financial gain, but also on social gains that could be associated with the service. Additional positive impacts are also associated with increasing innovation through open data and source material and by infrastructure and technology improvements. In contrast, potential negative externalities could be indicated by private companies gaining additional revenue from organisations that can least afford to pay a premium for their services and the need for cash-strapped organisations to allocate scare resources to data analytics. Each of these gains is discussed in detail below, however Table 4 provides a summary.

Many of the positive externalities resulting from the use of big data in crisis informatics revolve around the use of big data to provide positive impacts on the business models of humanitarian organisations with specific reference to providing better (E-PC-BM-2) and more targeted services (E-PC-BM-3) and to predict the needs (E-PC-TEC-1) of citizens affected by a crisis through improved situational awareness and enabling better resource allocation for humanitarian organisations (E-PC-BM-4). With respect to better services, the tool developed by the RICC provides humanitarian organisations with the "capacity" to "identify all of the

relevant information" on social media to react appropriately (Director, RICC, I-RICC-D). In addition, the IGO client said that a key improvement was in the efficiency of the information gathering to enable the process of establishing "who, what and where" more quickly (Programme Officer, IGO, I-IGO-PO) and to predict where resources will be required. Furthermore, individuals "feeding information" to the IGO enabled them to respond appropriately to "requests" on the ground.

Table 4: Economic externalities in crisis informatics

Code	Description	Relevance
E-PC-BM-2	Better services for members of the public in that the work of humanitarian organisations can be more efficient, they can provide relief faster and they can allocate their resources where the need is greatest.(I-RICC-D, I-RICC-PM, I-RICC-SS, I-IGO-PO, I-IHO-HP)	Improved situational awareness
E-PC-BM-3	More targeted services for citizens because the humanitarian organisations are reacting more quickly to information provided directly from the public. (I-RICC-D, I-RICC-PM, I-IGO-PO)	Improved situational awareness
E-PC-TEC-1	Identifying trends and needs using the tool for predictive purposes (I-IHO-HU)	Crisis preparedness
E-PC-BM-4	Better resource efficiency • organisations with technical capacity are analysing the data, leaving the humanitarian orgs to focus on relief • humanitarian organisations are able to target their activities to areas where there is most need or target response to needs. (I-IGO-PO, Focus group participants, I-RICC-D)	Better resource allocation
E-OC-DAT-2	Using open data to offer new services and fostering innovation by making the code open source (I-RICC-PM, I-RICC-D)	Social media innovation Open source computing
E-PC-BM-4	Need for additional resources for data experts (I-IGO-PO, I-RICC-D)	Distraction from core activities
E-OC-BM-8	Private companies benefiting from models by offering utilities (End-user, Focus group)	Infrastructure needs

Such targeting of services also enables humanitarian organisations to use their resources more efficiently. This may occur through outsourcing data analytics and focusing on their core activities. For example, the RICC notes that their artificial intelligence tool assists organisations with limited resources to use the full set of information coming in:

> If you think about how much time it would take one person to every week go through a few thousand text messages…if you have limited resources as it is, they want another option especially since they want the scale. And they are not going to be able to [analyse that data to the extent they would like]. (Director, RICC, I-RICC-D)

Automated systems also allow clients to take advantage of the analysis of a diversity of data that "is well beyond sort our capacity and generally our budget to handle" (Programme Officer, IGO, I-IGO-PO). This is especially important as the "core business" of humanitarian organisations is not data analysis and "it's very hard to convince management and say, okay I need somebody half the time working on artificial intelligence" (ibid., I-IGO-PO). Finally,

leveraging a corps of digital volunteers for the human computing component of the system also enables the RICC to capitalise on the ability of these volunteers to process information cheaply and quickly, particularly in time-sensitive situations like crisis.

Another positive externality in evidence in the case study is the use of open data to provide new services and providing open source material to support and foster innovation in data analytics (E-OC-DAT-2). This is slightly different to the externality code provided in Appendix A as, in addition to using open data provided by private companies, it also includes the provision of open source code from the academic sector. The economic externalities associated with using Twitter data to provide new services are discussed in detail in the section above. However, considering material from the technical challenges section demonstrates that Twitter features so prominently precisely because it is open, and other social media services like Facebook are vastly more difficult to access. In addition, the RICC also provide open access to their source code through services like GitHub to enable others to contribute to the development of their code and to enable others to build on their innovations. However, while this remains a potential gain, the RICC are not yet realising that benefit:

> The code and the documentation is such that anybody can come in and suggest improvements in the code and say I have got this extra module that will do that. […but] we are nowhere close to that. […] Maybe by the end of the year, early next year we will have something that I think all of us will be proud to call open source. (Director, RICC, I-RICC-D)

Nevertheless, this externality (E-OC-DAT-2) is heavy with potential, particularly as the use of big data in crisis informatics develops further.

The use of big data in this sector is also associated with potential negative economic externalities. Indeed, the positive effect of better resource efficiency (E-PC-BM-4) is challenged: data from the RICC and the IGO suggest that the popularity of big data and its increasing integration into crisis management activities mean that all organisations will require an injection of resources to meet this growing demand. This is particularly important for humanitarian organisations that may not have many resources to spare. In addition, given the infrastructural challenges associated with data storage, many data analytic providers are turning to large-scale corporate entities for services. According to focus group participants, this may result in resources provided by tax payers and philanthropists to humanitarian organisations ultimately being used to benefit large technology and other companies.

Thus, this analysis indicates that the use of big data in crisis informatics is primarily associated with positive economic externalities such as improved service delivery and resource efficiency for cash-strapped organisations. However, it is also associated with negative externalities such as the need to devote resources to additional competencies outside an organisation's core area of focus in order to "keep up" with big data and a potential that large companies with significant resources also benefit from these developments. Significantly, many of these economic externalities also implicate legal issues (data access), political issues (corporate subsidies) and social and ethical issues.

3.2 SOCIAL & ETHICAL EXTERNALITIES

The discussion above demonstrates that the use of big data in crisis informatics is associated with a number of positive social and ethical externalities folded into the discussion of the change in business models. For example, improved humanitarian services (E-OC-ETH-1) demonstrate a clear social and ethical gain for society, as the Programme Manager for RICC

argues, "if it's already happening at a business level, if it's already happening at a security or government level, why shouldn't it happen at a humanitarian level?" (I-RICC-PM). While these externalities will not be repeated, this analysis indicates both additional positive externalities and a series of potential negative externalities that are raised by the use of social media data in crisis informatics. In addition, in some cases, this discussion includes measures that are being used to mitigate these potential negative impacts.

Table 5: Social and ethical externalities in crisis informatics

Code	Description	Relevance
E-OC-ETH-1	Operations that increase citizen safety and provide essential relief (I-RICC-PM, I-RICC-SS, I-RICC-S, I-RICC-D, I-IGO-PO, I-IHO-HU, I-IHO-HP)	Humanitarian relief
E-OC-ETH-2	Development of tools and procedures to ensure ethical data practices (I-RICC-PM, I-RICC-SS, I-RICC-S, I-RICC-D, I-IGO-PO, I-IHO-HU, I-IHO-HP)	Ethical data processing
E-OC-ETH-9	Private data misuse by sharing the information without consent or using it for purposes that social media users may not have foreseen (I-RICC-PM, I-IHO-HU, I-IHO-HP)	Ethical data processing
E-OC-ETH-3	Invasive use of information, especially sensitive information (I-RICC-PM, I-RICC-SS, I-IHO-HU, I-IHO-HP)	Ethical data processing
E-OC-ETH-13	Misinterpretation of information or incomplete data can result in incorrect conclusions (I-IHO-HP)	Situational awareness
E-OC-ETH-4	Potential for discrimination (Focus group)	Equality

One of the potential positive externalities related to social and ethical issues is an increased awareness around the need for socially responsible and ethical data practices, and the development of tools to ensure ethical data practices (E-OC-ETH-2). RICC are working with other organisations, such as the ICRC, UN OCHA and well-respected universities to develop tools and procedures to promote and ensure ethical data practices. The Programme Manager for the RICC is heavily involved in this work:

> I worked on a project called the ethics of data conference where we brought in one hundred people from different areas of knowledge to talk about data ethics. And to infuse our projects and understand and build road maps. There is something called responsible data forum which is working on templates in projects, to be able to help people incorporate those kind of personal data. My colleague has been working on something called ethical data checklists as part of the code of conducts for the communities that he has cofounded. So these code of conducts I have written one for humanitarian open street map about how we manage data. (I-RICC-PM)

This collaborative work has resulted in a number of tools and procedural standards to ensure ethical data practice. Specifically, RICC subject every project to a risk assessment that includes a consideration of what will and will not be done with the data, what data will be stored, what data will be published. They also abide by the following rules: "we don't retain personal information, we don't share personal information" (Programme Manager, RICC, I-RICC-PM). They also edit the data so that different stakeholders get access to a different degree of detail. For example, for the maps provided to the media "you can only see only the colour and the map we provide to the [client has] a table with all these fields with the text, the actual text of the tweet" (Senior scientist, RICC, I-RICC-SS). In addition, they also screen the digital volunteers to ensure that there is nothing in their profile that would make the human element of the computing vulnerable to unethical practice. This includes asking them:

> [T]o provide links to a certain number of profiles, which could then be reviewed. So your Twitter account, your Facebook account, your LinkedIn, so essentially how you answer certain kinds of questions. Sort of where are you from? What is your nationality? Some basic kind of questions, your thoughts on the crisis and so on. And then, you know, LinkedIn, Twitter or Facebook or something, individuals from the tasking teams could go and review these people publicly and see okay what kind of things are they saying on Twitter? […] and then those people […] would be monitored. (Director, RICC, I-RICC-D)

This process ensures that the RICC is able to identify and rectify any potential conflicts of interest in the data analytics. Finally, the RICC also have an assessment tool to control the organisations and circumstances in which they deploy the artificial intelligence tool. This includes the following:

> the humanitarians have to show a very clear compelling need for this data and have to articulate very clearly how they are going to use this data and how it's going to make a difference. That is part of the application criteria, so in a way we rely on that demand-driven model. If they pass the test, if they pass our criteria then we are assuming that they are not lying through their teeth and are desperate for this data and it is actually for them. (Director, RICC, I-RICC-D)

This process is necessary to prevent the tool being used by unauthorised organisations for non-humanitarian purposes, e.g., for brand monitoring, etc. These ethical processes are particularly designed to prevent unethical data practices, such as those potential negative externalities discussed below.

The RICC interview participants, their clients and the focus group participants all recognised that the use of social media data to augment humanitarian relief services raised a number of potential negative externalities. These included the misuse of information (E-OC-ETH-9), misuse of sensitive information (E-OC-ETH-3), the potential misinterpretation of data and potential for discrimination (E-OC-ETH-4). With respect to data misuse, this was related to public authorities, the media or other organisations potentially misusing the information. Thus, this misuse may be linked to the private sector, but this was not always the case. Specifically, posting some information on the Internet can make individuals vulnerable. For example image data in political crises may require filtering and protection because:

> [Y]ou are not sure if the people being arrested actually want everybody, their family, their employers and everyone to know that they were at the demonstration and they were arrested. Especially, for example, this means that they may lose their job if their employer discovers that they were at the demonstration or, […] somebody being arrested and appears the next day, raises a lot of suspicion. (Head of Project, IHO, I-IHO-HP)

The IHO further warns that the posting of information on social media has significant consequences for those who appear in visual images, but who may not have provided informed consent for their image to be distributed. In addition, mapping activities also have to take into account the potential sensitivity of the places and data being mapped. The IHO also notes that in crisis or conflict situations you may have shelters for women or unaccompanied minors. You want to publicise this information for people who are in need, but you do not want to introduce additional vulnerabilities for these groups. As the RICC notes, this is strongly linked with issues around informed consent, as people who Tweet about these disasters may not expect their information to end up in the newspaper or other media (Senior scientist, RICC, I-RICC-SS).

There are also potential issues around the misinterpretation of data and the potential consequences of that (E-OC-ETH-13). Specifically, using the data without the contextual information that was used to collect the data can result in a "data gap" where the data becomes divorced from the context in which it was created.[6] The IHO notes "because you have the data you tend to forget how it was constructed and you tend to have results on things that don't mean anything" (I-IHO-HP). The IHO provides a specific example of this:

> In this case we had data on attacks on medical personnel and we had an indication also on the fact the healthcare person, whether it was a man or a woman. It has some relevance for us of course. But you cannot do it have an analysis if gender plays a role or not because we don't have the baseline country by country [information] to know what are the proportion of the male or female nurses, male or female doctors in [each] different area. And to know if there is a discrepancy between that baseline and the victims of an incident. […]There is a risk that if you then for example pass the set of data to someone else and someone else ask you to make an analyse of the data without really understanding the construct of the data the limitation the bias that might be there. (Head of Project, IHO, I-IHO-HP)

This demonstrates that there is a clear need with respect to any secondary use of data to interrogate the use of data and ensure that any residual misinterpretations, biases and misrepresentations are sufficiently examined and identified to prevent the sharing of misinformation and the erroneous allocation of resources.

The final potential negative impact, potential for discrimination, was not raised in the interviews, but was heavily discussed in the focus groups. This may be related to the fact that the RICC team was very transparent about the gaps in the data that they provide. However, focus group participants were looking at crisis informatics more broadly and they were concerned about issues related to discrimination. First, with respect to data sharing on an institutional and national level, a participant from an international data centre noted that it was difficult to integrate countries with fewer digital skills and less developed infrastructure. This has a clear knock-on effect in crisis informatics, if the data for specific locations is less detailed, mature and available. Second, with respect to social media in particular, focus group participants expressed concern that the digital divide could result in already vulnerable populations becoming more vulnerable. Specifically, communication with individuals on the ground would necessarily favour those with better access to digital devices, skills to use them and often English language ability. Thus, communication cannot be equally distributed among the population, either in terms of data collection or information distribution. There was also concern about irresponsible governments using the data to conduct surveillance on the population and identify those who were engaging in protest, unauthorised information sharing and other activities.

3.3 LEGAL EXTERNALITIES

Many of the legal issues discussed by interview and focus group respondents related to issues already discussed in previous sections, specifically privacy and data protection infringements as well as data ownership and access to proprietary data. It is clear from this analysis that both issues are represent both positive and negative impacts as the crisis informatics case study. For example, privacy and data protection infringements are possible, but different organisations are using established standards and protocols to introduce protective measures. In addition, while

[6] Royal Society, Science as an open enterprise, London, June 2012. https://royalsociety.org/~/media/royal_society_content/policy/projects/sape/2012-06-20-saoe.pdf

organisations have difficulty accessing proprietary data, this indicates that protections in this area are being respected. We report in Table 6 additional externalities corresponding to the legal category.

Table 6: Legal externalities in crisis informatics

Code	Description	Relevance
E-PC-LEG-4	Privacy and data protection threats specifically related to legislation (I-RICC-D, I-RICC-SS, I-RICC-PM)	Protection measures are in place, but their adequacy has yet to be tested
E-PC-LEG-5	Data ownership and proprietary data sets (I-RICC-D, I-IGO-PO)	Protection measures are functioning, but preventing access to additional data

As indicated in the social and ethical issues section, privacy and data protection infringements can result in significant effects on individuals and organisations. However, that section also noted that experts and practitioners were devising measures and protocols to mitigate this threat. Organisations are legally required to meet privacy and data protection laws in the countries in which they are operating, but in global data flows such as that represented by the work undertaken by the RICC, it is difficult to know which jurisdictions are relevant. In order to combat this difficulty, the RICC instils protection measures that are broadly applicable to a number of different major jurisdictions and which represent agreed good practice as developed by other major organisations in institutions. For example, as already noted, the RICC follow the International Committee of the Red Cross's (ICRC) data protection protocols, which include removing Twitter handles, personal identifying information and original tweets in the public version of the maps (Director, RICC, I-RICC-D). Instead, all that is visible in the final, public version are the categories. According to the RICC Director, this was in response to issues round informed consent. However, the RICC also stress that they are a "research institute" and that it is the responsibility of their clients to decide on the data protection measures and that it would be inappropriate for the RICC to "write the standards of data protection" (Senior scientist, RICC, I-RICC-SS). Nevertheless, they do alert clients to these guidelines and recommend that they are respected. According to focus group participants, this sort of practice is essential to win public trust that the processes being undertaken are legally compliant.

With respect to access to proprietary data the use of Twitter and the lack of integration of data from other media sources represents both a positive and negative externality. First, the RICC situation demonstrates that it is possible to use existing legislation to effectively access and analyse social media data. Combined with the lack of integration of other sources, this demonstrates that existing intellectual property mechanisms are working effectively:

> The challenge we face and why we often don't end up pulling much yet from groups like Facebook and Instagram is that we very much respect their terms of use or use of service or whatever they call it. Where it is actually very hard for us to I don't know if legally is the right word, but legally access their content and turn around and use that. So we have had some early discussions with them about trying to figure out how to, at least their public feeds to be able to use any of that kind of content. So at the moment we simply don't pull from them because we

> are not allowed to. And so we are not going to try and cross that border or that barrier until they give us approval. (Programme Officer, IGO, I-IGO-PO)

However, outside of social media particularly, focus group participants also noted that it was difficult to access information outside of crisis situations. While data access is almost universally granted during crises, the lack of availability outside of crises makes it difficult to put appropriate mechanisms in place to effectively analyse that data when it is available.

However, it was clear across all of the data gathered that big data analytics in crisis informatics would benefit from clear (and possibly new) legal frameworks in order to address externalities such as privacy, data ownership and also enhance and formalize how to share data among countries. While the need to clarify or develop new legal frameworks and protocols was classified as a negative externality, concurrently the discussion of these frameworks and current attempts to bridge them also simultaneously represents a positive development.

3.4 POLITICAL EXTERNALITIES

Finally, the international character of crisis informatics, including crisis response, humanitarian aid and development, often necessitates a cross-national flow of data, particularly when international humanitarian organizations are involved. However, politics in this area, and political externalities extend beyond international politics and also include political economics as they relate to tensions between for-profit organizations and humanitarian organizations. These are primarily negative externalities as they introduce vulnerabilities and they prevent effective collaboration between the private sector and the public or humanitarian sectors – they are included in Table 7.

Table 7: Political externalities in big data in crisis informatics

Code	Description	Relevance
E-OC-BM-8	Difficulty of potential reliance on US based infrastructure services (I-RICC-D) Tensions between private companies and public sector or humanitarian organisations (I-IGO-PO, I-RICC-SS)	Control over data use and service provision

Partnerships between large private companies and other organisations can be a positive externality in that it provides a cost-effective solution to infrastructure and technology issues. For example, the RICC is looking to solve their data storage problem by taking advantage of cloud storage solutions offered by Google and Amazon (Director, RICC, I-RICC-D). Similarly, such partnership can provide technological capabilities during crises that benefit the humanitarian sector in general – Google person finder is an example of this.

However, such partnerships also introduce potential negative externalities. Specifically, BYTE D2.1 has already indicated that the hosting of data on US soil or by US services means that the data becomes subject to US law, which introduces a vulnerability for people whose records are contained within those data sets.[7] Second, humanitarian organisations report being placed in a

[7] Donovan, Anna, Rachel Finn and Kush Wadhwa, Sertac Oruc, Claudia Werker and Scott W. Cunningham, Guillermo vega Gorgojo, Ahmet Soylu, Dumitru Roman and Rajendra Akerkar, Jose Maria Garcia, Hans Lammertant, Antonella Galetta and Paul De Hert, Stephane Grumbach, Aurelien Faravelon and Alejandro Ramirez, *Report on legal, economic, social, ethical and political issues*, BYTE Deliverable 2.1, 30 September

vulnerable position vis-à-vis private companies who promise "amazing solutions" or provide "their own huge amount of data and response to crisis" but who become unpredictable outside of the crisis situation (Programme Manager, IGO, I-IGO-PO). Furthermore, these organisations use their crisis activities to promote their own brand and socially responsible behaviour rather than truly engaging with the humanitarian organisations. Yet at the same time, such unpredictability can offer an opportunity for organisations such as the RICC. An RICC Senior scientist explains:

> Humanitarian organisations and others are very worried about creating technology dependence one particular vendor, so they find that our platforms are open source make them more comfortable with adopting our process and our technology because they know that we don't hold a leverage over their activity (I-RICC-SS).

Thus, the open source nature of the RICC project and tools make them more trustworthy in the eyes of humanitarian organisations who are more likely to adopt their solutions.

Summary

This analysis of potential positive and negative externalities has demonstrated that much like the general externalities examined in D2.1, the externalities associated with crisis informatics are overlapping and interconnected. Many of the economic innovations associated with positive changes in business models are also linked with positive social and ethical issues, including improved services for people who are vulnerable in a crisis or better resource allocation to enable responders to stretch their resources further. In addition, many of the potential negative societal externalities are associated with privacy, discrimination and the protection of personal data, which also implicate relevant legal frameworks. This has important implications for the development of recommendations to meet these challenges across the big data ecosystem.

4 CONCLUSION

The analysis of the use of big data in crisis management has indicated a number of key findings. First, big data practitioners in crisis informatics are relatively unconcerned about the "big data" label, and prefer to talk about data challenges, which are augmented by the size of the data being analysed. However, this preference may be related to the fact that crisis informatics is heavily concerned with social media data, which is certainly high-volume and high-velocity, but which does not integrate multiple data types. Perhaps as the sector matures with respect to integrating multiple data sources, including especially image data which is a high priority for the case study, the different aspects of "big" data may bring these issues to the forefront.

Second, the use of big data in crisis management raises positive societal externalities related to economic issues and social and ethical issues. These include especially, the better provision of humanitarian relief services, the provision of better, more targeted and more timely social services and better resource efficiency in providing these services. A significant facet of this is the collection of reliable information, on the ground, much more quickly to aid the situational awareness of the humanitarian organizations. The use of big data in crisis informatics also represents significant innovation potential due to the commitment to open data and open source computing, which will likely foster added innovations beyond the work of the RICC. In

---

2014. http://byte-project.eu/wp-content/uploads/2014/10/BYTE-D2.1_Final_Compressed.pdf

addition, while the use of social media certainly raises significant issues with respect to privacy, data protection and human rights, these issues are central to the way that data is being handled within the RICC and other organizations, and the case study makes clear that experts in this area are committed to ensuring ethical data practices within crisis informatics.

Nevertheless, some negative societal externalities remain, which must be addressed in order to ensure the societal acceptability of these practices. First, with respect to economic issues, the integration of big data, or data analytics, within the humanitarian, development and crisis fields has the potential to distract these organizations from their core focus and may represent a drain on scarce resources. In addition, there is a tension between private companies with extensive data analytics capabilities and humanitarian and other relief organisations. Humanitarian organisations are increasingly frustrated with private companies arriving during crises and leaving once the crisis has finished, without sharing or further developing the technological tools and capabilities that they introduced. Furthermore, they are also concerned about being dependent upon them for infrastructure, technological capabilities or other resources, as these organisations have proven to be unreliable partners. Finally, there are also significant, remaining privacy, legal and ethical issues around the use of data generated and shared by people through social media. While this sector has taken significant steps in this area, much work remains to be done in relation to the unintentional sharing of sensitive information, the protection of vulnerable individuals and the potential for discrimination that could result from this data processing.

CULTURE CASE STUDY REPORT

SUMMARY OF THE CASE STUDY

The utilisation of big cultural data is very much in its infancy. Generally, this is because data driven initiatives are focussed on cultural data to the extent that there is open access to digitised copies of cultural heritage works, rather than a broader focus that incorporates usage of associated cultural data such as transaction data and sentiment data.

The BYTE case study on big data in culture examines a pan-European cultural heritage organisation, pseudonymised as PECHO. PECHO acts as the aggregator of metadata and some content data of European cultural heritage organisations. The big cultural data case study provides a sector specific example of a data driven initiative that produces positive and negative impacts for society, as well as underlining a number of prominent challenges faced by such initiatives. Some of these challenges include potential and perceived threats to intellectual property rights and the establishment of licensing schemes to support open data for the creation of social and cultural value.

Although there is some debate as to whether cultural data is in fact big data, this discussion evolves as the volume, velocity and variety of data being examined shifts. PECHO, for example, utilises data that appears to conform to what is accepted as big data, especially when the data refers to metadata, text, image data, audio data and other types of content data that, once aggregated, require big data technologies and information practices for processing.

The case study also focuses on the variety of stakeholders involved and the roles they play in driving impacts of big cultural data. The execution of such roles, in turn, produces a number of positive and negative societal externalities.

1 OVERVIEW

The BYTE project case study for big data in culture is focused primarily on big cultural metadata. In the context of BYTE, big cultural data refers to public and private collections of digitised works and their associated metadata. However, a broader view of big cultural data would also extend to include data that is generated by applying big data applications to the cultural sector to generate transaction and sentiment data for commercial use. Thus, big cultural data includes, but is not limited to: cultural works, including digital images, sound recordings, texts, manuscripts, artefacts etc; metadata (including linked metadata) describing the works and their location; and user behaviour and sentiment data. Currently, utilisation of big cultural data is focussed on the digitisation of works and their associated metadata, and providing open digital access to these data. However, a focus on cultural data to include commercial revenue generating data, such as transaction data, is likely to develop both in the public and private sectors.

PECHO primarily deals with open linked metadata to make cultural data open and accessible to all Internet users. In turn, this initiative adds cultural and social value to the digital economy through virtual access to millions of items from a range of Europe's leading galleries, libraries, archives and museums. The relationship between metadata and content data at PECHO is described as, “So in [PECHO] you find metadata and based on what you find in the metadata,

you get to the content."[8] This case study also illuminates the social and cultural value of metadata, which is often overlooked, as it is not value that can be assessed in the traditional economic sense. PECHO facilitates access to Europe's largest body of cultural works. It does so in accordance with the European Commission's commitment to digitising cultural works and supporting open access to these works in the interest of preserving works of European cultures.

The relationship between PECHO and national and local cultural heritage museums is as follows:

> [PECHO] works as the EU funded aggregator across all cultural heritage, across libraries, archives museums. They only focus on stuff that has been digitised. So […] they don't work with bibliographic information at all, […] Anyway about 3 / 4 years ago […] they looked at various issues around digitalisation in Europe. And one of the conclusions that they came up with was that, all metadata should be completely open and as free as possible. [PECHO] took this recommendation and they came up with their [PECHO] licensing framework which asked all their contributors in the cultural heritage sector to supply their metadata cc zero.[9] This relates to both catalogue data and digital images and other content.[10]

Given the number of institutions involved and the variety of data utilised, this case study presents a number of opportunities to assess the practical reality cultural data utilisation by a public sector organisation. This includes gaining an insight into the technological developments in infrastructure and tools to support the initiative, as well as the technical challenges presented by it. It also provides insight into the issues such as funding restrictions, as well as the positive social externalities produced by committing to providing European citizens with open linked cultural metadata. PECHO also provides a solid example of the legal externalities related to licensing frameworks and the call for copyright law reform. Lastly, PECHO provides an interesting insight into political play between national and international institutions and their perceived loss of control over their data.

1.1 STAKEHOLDERS, INTERVIEWEES, FOCUS GROUP PARTICIPANS AND OTHER INFORMATION SOURCES

There are a number of stakeholders involved in PECHO, including local, regional and national cultural heritage organisations and their employees, data scientists, developers, legal and policy professionals, funding bodies and citizens. This is not an exhaustive list of big cultural data stakeholders per se and as big cultural data use and reuse is increasingly practised, the list of prospective stakeholders will expand. This is particularly relevant for the use of cultural data for tourism purposes, for example, which will involve more collaborative approaches between public sector and private sector stakeholders. PECHO-specific stakeholders were identified during the case study and include the organizations in Table 8.

[8] I2, Interview Transcript, 5 December 2014.
[9] Interviewee 1, Interview transcript, 27 November 2015.
[10] I2, Interview Transcript, 5 December 2015.

Table 8 Organizations involved in the culture case study

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
National cultural heritage institutions, including libraries, museums, galleries, etc.	Cultural	Late majority to Laggards	Acquisition, curation, storage,	Factory role
National data aggregator	Cultural	Late majority	Acquisition, curation, usage	Support role, factory role, strategic role
Pan – European cultural heritage data	Cultural	Early majority	Acquisition, analysis, curation, storage, usage	Support role, factory role, turnaround role, strategic role
Policy makers and legal professionals	Government	Late majority	Usage	Strategic role
Citizens	Citizens	Early adopters, Early majority, Late majority and Laggards	Usage	Support, factory, and turnaround roles
Educational institutions	Public sector	Early majority	Acquisition, curation, usage	Support role
Open data advocates	Society organisation	Early adopters	Usage	Support and turnaround roles

Interviews for the PECHO case study were the main source of information for this report. These interviews were supplemented by discussions held at the BYTE Focus Group on Big Data in Culture, held in Munich in March 2015. The interviewees and focus group participants referenced for this report are detailed in Table 9. Desktop research into big data utilisation in the cultural sector has also been undertaken for the BYTE project generally and more specifically for the purpose of providing a sectorial definition of big cultural data for Work Package 1.

Table 9 Interviewees of the culture case study

Code	Organization	Designation	Knowledge	Position	Interest	Date
I1	National library	Project officer	Very high	Supporter	High	27 November 2014
I2	Pan-European digital cultural heritage organisation	Senior operations manager	Very high	Supporter	Very high	5 December 2014
I3	National Documentation Centre, EU Member State	Cultural data aggregation officer	Very high	Supporter	Very high	9 January 2015
I4	International	Officer	Very high	Supporter	Very high	19 January 2015

	open data advocate foundation			/ opponent		
I5	Pan-European digital cultural heritage organisation	R&D officer –technology and infrastructure	Very high	Supporter	Very high	19 January 2015
I6	Pan-European digital cultural heritage organisation	Senior R&D and programmes officer	Very high	Supporter	Very high	30 January 2015
I7	Pan-European digital cultural heritage organisation	Senior legal and policy advisor	Very high	Supporter	Very high	20 March 2015
FG8	Academia	Information processing and internet informatics scientist	Very high	Supporter	Very high	23 March 2015
FG9	Institute of technology	Academic	Very high	Supporter	Very high	23 March 2015
FG10	National library	Data aggregation officer	Very high	Supporter	Very high	23 March 2015
FG11	University	Digital director	Very high	Supporter	Very high	23 March 2015
FG12	National Policy Office	Senior policy officer	Very high	Supporter	Very high	23 March 2015
FG13	Private sector cultural data consultancy	Partner		Supporter	Very high	23 March 2015

1.2 ILLUSTRATIVE USER STORIES

Pan-European digital cultural heritage organisation - PECHO

PECHO is, in essence, an aggregator of aggregators with around 70 aggregators currently working with them. These collaborations support the general running of PECHO as an initiative, as well as working together on specific data projects. PECHO is an aggregator "that works together with institutions to process their data in the best and meaningful way, either from the domain perspective or […] working for them to process data."[11] Additional project work is undertaken by PECHO in the utilisation of cultural metadata and is equally important because "these projects can also solve issues in many areas, be it working on new tools or finding ways to deal with Intellectual Property Rights holder issues, or making connections with creative industries to start making data fit for a specific purpose, all these things can happen in these projects."[12]

[11] I2, Interview Transcript, 5 December 2014.
[12] I2, Interview Transcript, 5 December 2014.

Policy and legal advisor – cultural data sector

The main focus of the policy and legal department at PECHO is to support the openness of metadata through the drafting and implementation of appropriate policies and licensing frameworks. PECHO is currently publishing up to approximately 40 million objects and it is essential to ensure that these items are appropriately labelled for licensing purposes. This because the PECHO model is,

> built on the fact that metadata should be open, it should be available under creative commons public domain dedication. And all of the content that is shared should be labelled with a statement that indicates how it can be accessed and what its copyright status is. And so those fundamental principles when change but maybe how we implement it will responds according to need.[13]

To that end, PECHO recently introduced a works directive to make sure data providers understand how to properly label cultural works, subject to any legal requirements.

R&D – Technology and infrastructure

The PECHO data model must facilitate the exchange of data resources. Data models for PECHO were created by looking at various models, the information that was available, and what data needed to be exchanged. This development process is described:

> we made some proposals and we started to implement the models for exchanging some vocabularies and also build some application that will show the benefits of exchanging that data. And what has happened in PECHO and communities some sort of drive, some sort of push to have this sort of technology deployed widely. And to have everyone who have these and publish them a bit more openly and easier to exploit from a technical perspective.[14]

The technical platform implemented to achieve this openness involves a number of players:

> So a part of the PECHO network is made of experts in technical matters, so either in the cultural institutions or in universities […] and our role is to facilitate their activities so part of it is indeed about while making sure the R and D network is more visible than what it used to be. And to promote well their activities and make their life easier.[15]

Research & Development personnel are tasked with pushing the development of this technology and developing the accompanying best practices so that more of the domain is made available to encourage data re-use.

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

The BYTE case study focuses on the publicly funded cultural data initiative and such, the discussion below relates the data sources, use and flows in that context.

2.1 DATA SOURCES

PECHO deals primarily with big cultural metadata (including open linked metadata) pertaining to cultural works (digital images, sound recordings, texts and manuscripts etc.) from a large majority of Europe's cultural heritage organisations. This includes metadata relating to the following works: digital images, sound recordings, texts, manuscripts, artefacts etc. This metadata is provided by a multitude of national and local cultural heritage organisations,

[13] I7, Interview Transcript, 20 March 2015.
[14] I5, Interview Transcript, 19 January 2015.
[15] I5, Interview Transcript, 19 January 2015.

usually via a national aggregator that deals directly with PECHO. However, museums, archives and libraries are the main data sources.[16] PECHO deals with up to 70 aggregators that provide varying amounts of data subject to the volume of catalogue data held by the data partner cultural heritage organisations. One representative of PECHO estimated the volume of data held:

> So at the moment we have in our database, […] 190 million metadata records, but they are not all open for various different reasons. And that includes […] 165 million bolographic records […] and we have 25 million records, which actually point to items that have been digitised.[17]

PECHO however does not store the data and nor do they wish to do so because "they are so diverse and they have lots of different peculiarities or properties that we only store the references to them. So it's a very high-tiered organisation […]"[18] PECHO provides access to up to 40 million items of open data, which has built up over 6 years. The figure is higher when the metadata that does not accord with the CC0[19] licensing requirement is added, together with the content data that PECHO links to. The volume of data continues to increase, although,

> we are not particularly calling for new content to be delivered […] you can say it just happens. Yes mainly it's that […] people come and give us data, and that's our regular partners and growing partners. That is always growing. So we don't go out and necessarily make open calls for more content etc.[20]

Some of the metadata are created and provided by experts. For example, librarians of national libraries provide lists of metadata relating to a particular subject matter. This constitutes a wide and rich body of knowledge.[21] However, PECHO does not accept any metadata from its data partners that is not provided under a CC0 licence and all data partners are required to sign a data agreement to that effect.[22] This is a fundamental requirement of the PECHO Data Model (PDM), which was developed in-house as a means of dealing with open linked metadata, especially as these data are often provided in a number of formats and languages. The PDM centres on the concept of open access and it has significantly contributed to the open data movement in Europe.[23] The PDM is specifically designed to aid interoperability of data sets during the data acquisition phase. Integrating data into the PDM is an interactive process:

> So cultural institutions need to connect to what we call aggregate to switch our national or domain associations or organisations that collect data in their domain of their perspective countries. And they connect it according to the data model that we have set and we have provided that is called PDM, the PECHO Data Model, and this aggregation structure is like a tiered structure in which the cultural heritage organisation of which there are about 60,000 in Europe only alone, are being collected through about 50 or more aggregators […] that aggregate these data to us and we deal with them. The data itself in only the metadata so there are references to objects that are stored locally at the cultural heritage institutions.[24]

---

[16] I5, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[17] I1, Interview Transcript, 27 November 2014.
[18] I6, Interview transcript, 30 January 2015.
[19] CC0 License is a form of public license that releases works into the public domain with as few restrictions on use as possible.
[20] I2, Interview Transcript, 5 December 2015.
[21] I5, Interview Transcript, 19 January 2015.
[22] I2, Interview Transcript, 5 December 2014.
[23] I1, Interview transcript, 27 November 2014.
[24] I6, Interview Transcript, 30 January 2015.

The PDM also facilitates the richness of the data used by PECHO. The PDM:

> was developed over some time, and is not going to be implemented, and meanwhile a number of data projects and aggregators are also working with PDM and giving us a data PDM which allows them to make them more richer, which allows them to also incorporate vocabularies, so it's a much richer and much…it is yes…allows for more powerful than our previous scheme model that we used.[25]

Looking to the future, there may be additional sources of data, although these are not yet institutionalised in the PDM. For example, transaction data and public sentiment data can be utilised in the future, not just by PECHO, but by other organisations as well that wish to capture the benefits associated with that type of data in the cultural sector.[26]

2.2 DATA USES

The primary use of the metadata is to provide citizens, educational institutions and other cultural heritage institutions with efficient access to cultural heritage works and their related information. This is the primary use of big cultural data in the context of PECHO. Thus, the value of this data utilisation lies simply in making cultural and historical works available for use and re-use. PECHO facilitates this through the implementation of technological infrastructure and software specifically designed for the provision of open cultural metadata for the efficient location of content data.

Furthermore, the facilitation of open cultural metadata has lead to a number of subsequent uses of the metadata and content data. This bolsters the value of metadata, which is observed:

> metadata for us are still important they are a product and if we don't consider them as being a product then it becomes very difficult to raise a bar and also to make that content that are underlining this data properly accessible.[27]

Metadata and content data use and reuse are the primary focuses of the PECHO initiative. For anyone in Europe and abroad who wants to connect to cultural heritage data digitally, that use is facilitated by the PECHO centralised data model or centralised surface (the PDM). PECHO supports re-use of data by connecting data partners with creative industries, for example. This means that current and prospective stakeholders within these industries are aware of access to the catalogues, which in turn, can lead to works being re-purposed in a contemporary and relevant way. This re-use is supported by PECHO's commitment to open data "because we make the stuff openly available we also hope that anyone can take it and come with whatever application they want to make."[28] This is significant as the discourse on cultural data at present is about reuse, now that the practise of digitising cultural works is maturing. This means that "PECHO is thus experimenting if you like with how there can be a different infrastructure where they can hold extra content and whether value is created both for the providers and the aggregators and the intermediaries."[29] Furthermore, in the creative sense, PECHO provides a number of data use opportunities, including the following example:

[25] I2, Interview Transcript, 5 December 2015.
[26] See Deliverable 1.3 "Sectorial Definitions of Big Data", *Big Cultural Data,* 31 March 2015.
[27] I2, Interview Transcript, 5 December 2014.
[28] I5, interview Transcript, 19 January 2015.
[29] I3, Interview Transcript, 9 January 2015.

> we have PECHO sounds which is currently in its nascent stages, which is looking at more non-commercial sound recordings like folklore and wildlife noises and what have you. We're just about to launch a portal called PECHO research, which is specifically aimed at opening up and raising awareness of the use of data in the academic community. And we also have our PECHO labs website which if you are on our pro website which is the pink colour one, in the right hand corner I believe.[30]

Instructions for how users can reuse data are generally provided alongside the data, although typically, the data will be under CC0 license.[31] Aside from this use and re-use, the data are otherwise technically used in a manner that involves day-to-day data processing, including harvesting and ingesting.[32]

2.3 DATA FLOWS

There are a number of steps involved in making cultural metadata and content data available through the PECHO web portal.

First, data originates from cultural heritage organisations all over Europe, as discussed above under 'Data sources'. For example, a national library in Europe aggregates catalogue data for PECHO and provides it in the format prescribed by the PDM.

More generally, the data flows from the original source as it is described in the following example:

> we take metadata from a museum. They give us the metadata solely and in the metadata as part of the metadata they give us a URL to where their digital object is restored […] On their website, on their servers so that it can be publically accessible by PECHO. Now we don't store that object for that museum we just republished via the URL. So we only deal with metadata you are quite right. However our goal is to share data so metadata and content. And it is really important that if users find the metadata the museum provides and because they can see the images that are retrieved via image URL they need to be able to know how to use those images.[33]

Thus, all data are either channelled to PECHO via a national data aggregator or directly from the smaller institution. A team at PECHO acts as the interface with the partners across Europe that provide data to PECHO. They process these data internally until they get published in the PECHO portal. The data may then also become accessible via the API and other channels.[34]

The data flows are facilitated by the PDM referred to above. This process is described in more detail by a representative of PECHO who states that the PDM is a:

> one of a kind model which allows the linking and enrichment of the data so you could very much generalise data […] if you adhere to the PECHO Data Model you could link it to what multilingual databases. So for instance look for an object in a German language you would automatically find results that are described in English or any other European language. So it is

[30] I7, Interview Transcript, 20 March 2015.
[31] I7, Interview Transcript, 20 March 2015.
[32] I2, Interview Transcript, 5 December 2014.
[33] I7, Interview Transcript, 20 March 2015.
[34] I2, Interview Transcript, 5 December 2014.

> a lot aligned to the thesaurus model or the models that have been in place for years now. So that is the main feature I think of the PECHO Data model.[35]

In terms of data processing, the open data is given priority over data with a restricted license. Overall, the flow of cultural metadata at PECHO is ever evolving and is modified and developed to meet technical challenges as they arise. The main technical challenges are addressed below.

2.4 MAIN TECHNICAL CHALLENGES

The primary technological and infrastructural challenges that arise in relation to achieving the PECHO objective of providing open linked cultural metadata generally relate to the organisation, standardisation and alignment of the disparate data coming from a large number of varied institutions that use differing formats and languages. The primary solution offered by PECHO to their data partners is assisting them with their adherence to the requirements of the PDM.

Central to making cultural data accessible to a wide audience, the technical challenge presented by the diversity of European languages must be overcome. This is a primary issue because, "the difficulties we have at European libraries, of course, is that we across Europe are multilingual."[36] This challenge has been dealt with by incorporating methods of translation into the PDM in order to bring the data into the required format for mapping the data. Another technical challenges faced in relation to open data, is not in terms of facilitating openness, but rather, tracking how the open metadata and data is being used. PECHO must implement technical solutions that are capable of evolution so that the data can utilised. This challenge will likely be addressed as the PDM evolves. Moreover, participants at the BYTE Focus Group on big data in culture agreed that in-house development of solutions to technical challenges is required for total control over data, and especially if, in the future, stakeholders will better utilise transaction data and sentiment data to capture commercial benefits associated with big cultural data. However, these processes require considerable financial resources, which is an issue when dealing with public-sector data driven initiatives.[37]

The varying quality of data is also a technical challenge faced by the PECHO data processing team. This issue arises because every user has different requirements and differing perspectives on data qualities than the curator or data entry person that made the data in the first place. In the context of PECHO, data quality means:

> Richness is certainly part of it, like a meaningful title or a long and rich description and contextual information use of vocabularies and all these aspects to help making data more richer and easier to discover. But it has several also other areas, like, currently a lot of the metadata that we get, are made for a specific purpose in a museum in an archive, in the library, for example to by scientists for scientific purposes for example, this is why sometimes a lot of these data are generated for purposes and now they are turned into something how does it work for the end user. And how is it fit for even a reuse purpose, which sometimes is difficult to achieve as the starting point with a different one. So also depending on what you want with these data, you may get different […] definition of what quality is for you.[38]

[35] I6, Interview Transcript, 30 January 2015.
[36] I1, Interview Transcript, 27 November 2014.
[37] FG10 and FG11, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[38] I2, Interview Transcript, 5 December 2014.

Addressing this issue was the topic of a task force last year that examined metadata quality. Data quality remains important because PECHO needs to enforce its set of mandatory aspects of the PDM so that every record has an appropriate rights statement attached for the data object, as well as other mandatory fields for different object types, and text language/s. These standards enable PECHO to "leverage the full potential of the object type that we get, and achieve a certain level of consistency was yes basic data quality that we want to achieve." [39]

Overall, addressing technical challenges in-house and as they arise is key to the effectiveness and efficiency of the PECHO initiative:

> With incentives coming from creative with new technologies coming from cloud and from within our own organisation, working to make processes more efficient, that also some of these issues can be solved. These issues however are the key driver in technological innovation. PECHO also works with its data partners to solve some of the issues that you are mentioning in terms of infrastructure and resource. "For example data aggregator for museum would be in a better position to make the tooling, that would make mapping easier for the individual museums.[40]

2.5 BIG DATA ASSESSMENT

There is debate as to whether big cultural data exists.[41] Theoretically, we can consider the extent to which big data in the cultural sector contends with the accepted definitions of big data, such as the Gartner 3Vs definition or an extension of that definition, such as the 5Vs, used to assess big data across case study sectors in Work Package 1 of the BYTE project. The 5Vs include: *Volume; Variety; Velocity; Veracity;* and *Value*. These Vs are more likely met when cultural datasets are aggregated. Although there is some evidence of stand alone data sets being considered big data, such as sizeable collections held by cultural heritage organisations or in private collections. For example, the totality of cultural metadata utilised by PECHO would likely contend with a definition of big data. The following is an assessment of whether big cultural data exists in the context of the case study based on information gleaned during case study interviews and supplementary discussions held at the BYTE Focus Group on Big Data in Culture and assessed against the 5Vs of big data:

Volume can be indicated by: massive datasets from aggregating cultural metadata; or large datasets of metadata of cultural items available at cultural heritage institutions (museums, libraries, galleries) and organisations. PECHO holds 36 million data, which has built up over a period of approximately 6 years.[42] This volume was the product of an aggressive pursuit of data. However, the total volume of the data used or linked to via PECHO is roughly 190 million items and growing, and as such requires processing through the implementation of a data specific model, the PDM.[43] This likely contends with the volume element of a big data definition. Nevertheless, debate surrounds the volume of cultural data and a data scientist specialising in search engine technology and broadcast data who participated in the BYTE Focus Group opined that cultural data is not, in practice, considered big data, although it

[39] I2, Interview Transcript, 5 December 2014.
[40] I5, Interview Transcript, 19 January 2015.
[41] This topic attracted much discussion by big data practitioners in attendance at "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[42] I2, Interview Transcript, 5 December 2014.
[43] I6, Interview Transcript, 30 January 2015.

becomes so when a number of databases are combined.[44]

Variety can be indicated by: quantitative data, e.g. cataloguing of metadata and indexed cultural datasets; qualitative data, e.g. text documents, sound recordings, manuscripts, images across a number of European and international cultures and societies in a variety of languages and formats; and transactional data, e.g. records of use and access of cultural data items. The data held by PECHO is made up of all of these characteristics, particularly noting that the vast array of data items are provided in a variety of languages and formats.

Velocity can be indicated by: monitoring user behavioural and sentiment data, social media traces, and access rates of cultural data etc. This is not a major focus of the PECHO model, although it is becoming increasingly so.

Veracity can be indicated by: improved data quality. Data quality, richness and interoperability are major issues that arise in relation to the data used (and linked to) via PECHO. This is especially visible as every user has different requirements and differing perspectives on data qualities than the curator or data entry person that made the data in the first place. In this context, the veracity of the data used contends with that commonly accepted to indicate big data. Nevertheless, there exists contention around the veracity of cultural data and its richness.[45]

Value can be indicated by: knowledge creation from the access and potential re-use of digitised cultural items; improved access to metadata and data, e.g. historical texts; and improving efficiency for students, researchers and citizens wishing to access the data and reducing overall operational of cultural institutions and organisations. Although the value of cultural data is cannot be assessed in the traditional economic sense, does not mean that it does not generate social and cultural value.

The data utilised by PECHO constitutes big data in a manner that is best summed up a representative of PECHO: "we may not have really big data technically but we have heterogeneous data and we have scientific content."[46] Nevertheless, the definition of big data continues to change as computational models change, which makes it difficult to assess the 'size' of cultural data generally.[47]

3 ANALYSIS OF SOCIETAL EXTERNALITIES

This section examines the positive and negative externalities identified in the culture case study, according to the list of externalities included in Appendix A (see Table 55).

3.1 ECONOMICAL EXTERNALITIES

The immaturity of big cultural data is linked to its evolution in the public sector. The digitisation of items of cultural heritage is carried out largely by public sector institutions and organisations. This means that these processes are subject to policy and funding restrictions, which at times act as barriers to progress and the slow the adoption of big data information practices across the sector. Second, and again related to the public positioning of the cultural sector, there is a strong focus on deriving cultural and social value from the cultural data rather

[44] FG11, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[45] FG10 and FG11, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[46] I3, Interview Transcript, 9 January 2015.
[47] FG11, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.

than monetising these data or applying big data applications to generate profit in a commercial sense. This is one of the main reasons that associated data, such as transaction and sentiment data are not yet being fully utilised. In the case of PECHO, the generation of revenue is not at this stage a primary objective, and in any event, in this context, copyright laws restrict better utilisation of cultural data and its traction data.[48] Focus group participants also identified the negative impacts that are produced when new business models utilising big cultural data, such as competition and regulatory issues, or development and innovation are hindered as a result of a 'copyright paranoia'.[49] Thus, big cultural data is predominantly understood as a publicly funded investment in culture creation and preservation. This potentially hinders the economic externalities that would otherwise flow from big cultural data use and re-use.

In terms of economic value being derived directly from the metadata in a traditional economic sense, analysis shows there is no real economic value into the business of metadata directly by exploiting the metadata.[50] However, there are indirect economic benefits in that it raises the visibility of the collections and of the providers and drives more traffic to these national and local sites, which are the main value propositions for providers in terms of making their data available to aggregators.[51] However, the restrictive funding environment and stakeholders' inability to exploit metadata directly can act as barriers to innovation as well. An example of why funding plays a major role in the creation of externalities was provided by a representative of PECHO as being linked to the expense of adequate infrastructure: "Storage is very expensive that is what we noticed, it is not the storage itself but the management of the storage is really an expensive thing."[52]

Despite these issues, limited resources also drive innovation. Innovation is a crucial element of economies. PECHO provides examples of innovative collaborations, such as PECHO Cloud, which is predicted to have an impact in terms of the future of infrastructure, and aggregation for big cultural data. Innovation is also captured in the following description of a developing business model at PECHO:

> what we propose in the business model for PECHO cloud surfaces, is that we can do it just as expensive or just as cheap as the national aggregation services or domain aggregation services would do. But then on a European wide scale, so there is this automatic involvement in the infrastructure that we are proposing. Which has the advantage that anybody can access it under the conditions that we have set.[53]

Thus, PECHO's commitment to open data produces a number of economic opportunities. Furthermore, this is possibly the major impact of PECHO as the value lies in making the metadata open and accessible for repurposing. This means that datasets that are "glued" together by the semantic web community are currently being used by many people to fetch data rather than storing their own catalogue of data.[54] This also potentially enables stakeholders to create services, such as (online) guided tour models for tourism purposes, which prompt people to travel and view the original version of what they see online.[55] Other positive economic

[48] FG, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[49] I6, FG8, FG9, FG11 & FG12, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[50] I3, Interview Transcript, 9 January 2015.
[51] I3, Interview Transcript, 9 January 2015.
[52] I6, Interview Transcript, 30 January 2015.
[53] I6, Interview Transcript, 30 January 2015.
[54] I5, Interview Transcript, 19 January 2015.
[55] FG8, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.

externalities associated with the use of big cultural data can be: better trend prediction for marketing purposes (although this is not yet a focus of publicly-funded cultural data driven initiatives); innovation of cultural services; supports an ease of preservation of cultural heritage works; and more comprehensive studies of the works due to longer access periods, which can result in innovations.[56] Positive economic externalities produced by big cultural data utilisation were reiterated by focus group participants, namely when it is used in the creation of new applications and/ or business models for education or tourism purposes that combine cultural data and EarthObvs data. Big cultural data also aids journalism and data-enriched stories.[57]

Table 10 Economical externalities in the culture case study

Code	Quote/Statement [source]	Finding
E-PC-DAT-1	[…] A number of data projects and aggregators are also working with PDM and giving us a data PDM which allows them to make them more richer, which allows them to also incorporate vocabularies […] PDM is also taking up by other partners, like the Digital Library of America, LA, they have learned from this and have their kind of own version of PDM and so that the German Digital Library has done also something similar, has taken PDM and tried to use that in a way that it fits that purpose. So it's widely known and widely used also and something we have done, that's PDM. Otherwise thinking really technology and software and tools, I actually would be hesitant to say this is quite a narrative tool or software that we have done, and everyone else is using, because I'm not really into that business. Look at the German digital library example.	Innovative data models are being developed and adopted by external stakeholders.
E-PO-BM-2	[…] we rather thought of the data model as something we would make available for the benefit of all […] that may be difficult to start licensing it and make money out of it. Actually a lot of the extensions we make to the data model a lot of the updates are made. So process wise we do our own investigations […] and we do the updates and we make the model better or we directly call on our partners.[58]	Big cultural (meta)data is supported by specific infrastructure and tools for the provision of open data, which in turn, inspires innovative re-use, rather than the generation of the profit in the traditional sense.
E-PC-TEC-2	Data about events, people visiting sites are largely underused. Bringing that together becomes an advantage. Personalised profiles are important. Cross-linking of data adds value.[59]	Interaction data is largely underused when dealing with big cultural data,

[56] I6, FG8, FG9, FG11 & FG12, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[57] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[58] I5, Interview Transcript, 19 January 2015.
[59] FG12, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.

		despite its potential economic benefits.

3.2 SOCIAL & ETHICAL EXTERNALITIES

The overarching social externality associated with PECHO is the creation and enriching of cultural and social value for European citizens. This achieved by facilitating readily accessible cultural heritage data. One aspect of value creation is combination enrichment, supported by providing searchable open cultural data and metadata. This search ability also facilitates depth of research and study, which leads to greater insights and a more accurate presentation of cultural and historical facts.[60] However, this raises the ethics of opportunistic search engines being able to control interaction data relating to another organisations' efforts for their own commercial benefit. For example, Google is free but uses the information provided by PECHO in its own business model for targeted advertising. However, PECHO provides the service at a cost to the taxpayer where revenue generation is not always considered an appropriate aspect of the business model, in accordance with a public-sector ethos.[61] Thus, the social value created by open linked metadata also implicates ethical considerations of data exploitation and inequality. Further, inequality of access between organisations entails the situation where the publicly funded open data model provides private organisations with access to both these data, as well as their own data, which they are under no obligation to share. Public institutions, such as PECHO, have free access only to the data they hold and are limited in their potential use and repurposing of that data because of this.

Further, focus group participants identified the risk of fraud resulting from open access to cultural data when anyone with access to digital versions of cultural works may reproduce it or misrepresent (lesser known) works as their own, via social media for example. This is also because authenticity becomes difficult to verify when works are distributed on a mass scale.[62]

Lastly, the ethics of privacy were identified as a potential externality of open cultural data, insofar as privacy of individuals or groups identified in cultural data can be invaded via the provision of linked metadata. In the case of PECHO, any risk to privacy is addressed in the "terms of use" policy section on the website. Practically speaking, this means that, "if people think that something is not correct or they have problems with similar to Google, they can inform us and then we take the material also down."[63] Whilst threats to privacy are a potential issue, it is not a major concern in practice because it can be readily addressed and there are so few recorded complaints.[64]

Table 11 Social & ethical externalities in the culture case study

Code	Quote/Statement [source]	Finding
E-PC-ETH-1	The content is not accessible for searching. I mean when we have full text of course you can deploy full text search on top of it. But for pictures of paintings or statues or even sounds without metadata you can't do much for searching and accessing them. And that is often overlooked but it is true	The value of metadata is often overlooked**.**

[60] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[61] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[62] I6, FG8, FG9, FG11 & FG12, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[63] I2, Interview Transcript, 5 December 2014.
[64] I7, Interview Transcript, 20 March 2015.

	that in the past year […] everyone has come to realise that metadata is an important piece of the puzzle. And I believe that all these stories about national security actually kind of helped send a message. People are more aware of the benefits and the dangers of metadata.[65]	
E-PC-LEG-4	[…] suddenly where we get issues are when kind of privacy aspects are touched upon. Like pictures where somebody is on the picture, either the relative or the person themselves doesn't want this picture to be on line, so this is also when we get take down requests.[66]	In theory, the ethics of privacy are implicated by open-linked metadata.
E-PO-DAT-1	So actually when PECHO started providers where extremely reluctant and the data model were actually instrumental in convincing them. Because there is the idea we can produce we can publish richer data that can benefit everyone. But that will really happen if everyone decides to contribute because if everyone keeps their data for themselves then not much happens.[67]	Tackling inequality between public sector and private sector organisations will be instrumental in generating value for all stakeholders.

3.3 LEGAL EXTERNALITIES

Reuse of cultural data is not absolute and for cultural data to be lawfully re-used it needs to be done so in accordance with relevant legal frameworks. In fact, managing intellectual property issues that arise in relation to the re-use of cultural data is perhaps the biggest challenge facing big cultural data driven initiatives, such as PECHO. The effect of copyright protections, for example, can be a limit on sharing data (that could otherwise be used for beneficial purposes) and the enforcement of high transaction costs[68], which then restricts the audience members to a particular demographic.

Further, arranging the necessary licensing agreements to enable re-use of cultural data can be arduous, especially as there is limited understanding and information about how rights statements and licensing frameworks can support stakeholders in capturing the full value of the data. This not only includes the technological challenge of making the data truly open and accessible, but also necessitates an attitudinal shift amongst traditional rights holders, as well as cultural heritage organisations that hold cultural data. Licensing arrangements by the BYTE case study organisation, PECHO, are commonly tackled through applying a Creative Commons licensing regime, namely a CC0 public licence. PECHO Creative, a PECHO project, provides a good example of how transparent licensing arrangements can support open cultural data, which enables re-use and the benefits that flow from that reuse. The longstanding tensions surrounding intellectual property rights and cultural data has led to a strong call for copyright reform in Europe on the basis that the legislation is outmoded and a barrier to sharing and open data.[69] For example, an institution that stores terabytes of tweets from Twitter has been unable

[65] I5, Interview Transcript, 19 January 2015.
[66] I2, Interview Transcript, 5 December 2014.
[67] I5, Interview Transcript, 19 January 2015.
[68] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[69] I7, Interview Transcript, 20 March 2015.

to utilise that data for the purpose it collated the data due to the barrier to sharing presented by the current intellectual property framework.[70]

In addition, data protection was identified as a legal barrier to some models that incorporate the use of cultural interaction data, and for also limiting the re-use of certain forms of cultural data, such as data including references to sensitive personal material.[71] As this is an area of on-going debate, reform will continue to be pursued by stakeholders.

Table 12 Legal externalities in the culture case study

Code	Quote/Statement [source]	Finding
E-PO-LEG-2	One barrier that I'm not going to priorities but our rights, that's one thing that is always a difficult question for us. When it comes to rights people need to apply to actually also even know what the copyright situation is. That sometimes is causing interesting questions and discussions with partners on all levels.[72]	One of the major issues, and potential barriers to re-use of cultural data is property rights. However, this can arise as a result of miss-information or a lack of understanding held by the data partners.
E-PP-LEG-2	So this year we are looking again at rights statements and how those can be clarified because the legal landscape is difficult and it is difficult for users to sometimes understand what restrictions there might be when using content. […] We need to make sure that they are accurate but also they are kind of harmonised across Europe because we don't want 28 different ways to say something is in copyright. In the same way that Creative Commons who is a licensed standard that we use as a basis of a lot of our options. And Creative Commons even moved away from having 28 different or…it wasn't even 28 it was country specific licences. So in their recent update they moved away from country specific and just upgraded to 4.0 and then said that actually if you want to translate it you can but 4.0 in English it is one licence it is not adapted to any country specific law.[73]	Fragmented implementation of European intellectual property framework is jeopardising open data and the opportunities associated with the reuse of cultural data.

[70] FG11, "Big Data in Culture", *BYTE Focus Group*,Munich, 23 March 2015.
[71] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[72] I2, Interview Transcript, 5 December 2015.
[73] I7, Interview Transcript, 20 March 2015.

E-PC-LEG-5	It is an important balance to sharing the metadata the descriptive information because you want cultural heritage to be discoverable, which is why we believe it should be open. We want it to be reused but there is a very important rights holder issue here is that there's a lot of copy right in modern day and you know our culture and history that is up to about 140 years old. That has to be respected, you have to have permission in some way to access it or to reuse it and that has to be communicated. But in the same way there are also works that are 200 years or 300 years old were no copyright exists. So we took the decision that it is important to communicate that there are no restrictions as well. And this is the public domain mark, this says there are no copyright restrictions of course respect the author by attributing their information. But you are not bound by any copyright restrictions when you access when you want to use this work. And I think that the role of the right statements which are sort of big part of the licensing framework is to help educate users and to help communicate this information so that people…understanding of what they can do with the content that they discover via the metadata published on European.[74]	Cultural heritage organisations needs assistance with understanding the copyright framework.

3.4 POLITICAL EXTERNALITIES

Political issues arise in relation to making the data open because it can lead to a perceived loss of control of data held by national institutions thereby causing intra-national tensions. This tension is also fuelled by reluctance on part of institutions to provide unrestricted access to their metadata under a CC0 license. The immediate response to this for PECHO has been to include a clause in the Data Agreement requiring a commitment to sharing only metadata with a CC0 licence or be excluded from the pan-European partnership, and subsequently, lose the benefits associated with PECHO. However, this aggressive approach heightened fear of loss of data control by some stakeholders. Such tension between data aggregators and data partners are a direct political externality of promoting open cultural data. However, this is now being addressed through education and information providing initiatives at PECHO that highlight the importance of local contributions to the development of cultural data aspect of the European digital economy.

There also exists a EarthObvs-political tension around the American dominance over infrastructure. This has prompted a general trend towards reversing outsourcing practices, and developing infrastructure and tools in-house, as has been the case with PECHO.[75] For example, now organisations are developing their own search engines and downloading data from cultural heritage institutions.[76] This has also been driven out of a desire to maintain control over infrastructures and innovations, as well as retain skills and expertise in-house, and more specifically, within Europe. This has been an important shift in the attitude towards a more protective approach to European innovations and development.

[74] I7, Interview Transcript, 20 March 2015.
[75] FG8-FG13, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.
[76] FG11, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.

Aside from the aforementioned political externalities, political externalities in the context of BYTE case study otherwise arise indirectly when partisan priorities dictate the use of cultural data in the public-sector, especially in terms of funding.

Table 13 Political externalities in the culture case study

Code	Quote/Statement [source]	Finding
E-PP-LEG-1	[…] for instance that in Germany there is a law, which requires cultural heritage stored in the country itself. So if you are building a cloud structure for cultural heritage you need a mirror or a synchronised mirror in the country itself. And we need to provide access copies to them and there are also more of a political issue that many countries would like a national cloud surface developed. Just because they would like to have control of them and at PECHO are looking for a centralised surface that is run by us. But it needs to synchronise or it needs to mirror what is happening in the national aggregation surfaces.[77]	There are intra-national political issues related to a perceived loss of control of a nation's cultural heritage data.
E-PO-LEG-1	Call for a political framework around cultural heritage data to protect culturally sensitive data so that it is not leaked.[78]	There is an increased shift towards protectionism of cultural data and keeping infrastructure and technical developments local.

4 CONCLUSION

Big cultural data utilisation is in its infancy and as such, the full extent to which data utilisation in this context impacts upon society is not yet realised. There is also ongoing discussion as to whether cultural data accords with definitions of big data.

Nevertheless, the PECHO case study provides insight into how to big cultural data utilisation is maturing and the economic, social and ethical, legal and political issues that arise in relation to the aggregation of cultural metadata in the open data context.

PECHO has faced a number of technological challenges, but these challenges have also prompted innovation in data models, tools and infrastructure. Despite these challenges, PECHO produces a number of positive externalities, primarily the creation of social and cultural value. Similarly, legal issues related to intellectual property rights have prompted the drafting of in-house licensing agreements that can be used as models by similar data-driven initiatives. One of the more significant externalities to be produced by PECHO is the PDM, which has been adopted abroad and is indicative of the potential for innovation in data driven business models.

[77] I6, interview Transcript, 30 January 2015.
[78] I6, FG8, FG9, FG11 & FG12, "Big Data in Culture", *BYTE Focus Group*, Munich, 23 March 2015.

Overall, the externalities produced by big cultural data utilisation have lead to a number of overarching conclusions. First, copyright reform is necessary to enable cultural data sharing and openness. Second, there is a real need for data scientists to grow this aspect of European data economy and retain the skills and expertise of local talent, which in turn, will limit control by organisations from abroad, such as those run by US-base stakeholders. Third, larger cultural datasets require more informed data quality practices and information about data sources and ownership. Therefore, the BYTE case study on big cultural data utilisation provides a practical example of real challenges faced, and externalities produced (or pursued) by a publicly funded cultural data initiative.

ENERGY CASE STUDY REPORT – *EXPLORATION AND PRODUCTION OF OIL & GAS IN THE NORWEGIAN CONTINENTAL SHELF*

SUMMARY OF THE CASE STUDY

This case study is focused on the impact of big data in exploration and production of oil & gas in the Norwegian Continental Shelf. We have interviewed senior data scientists and IT engineers from 4 oil operators (oil companies), one supplier, and the Norwegian regulator. We have also conducted a focus group with 7 oil & gas experts and attended several talks on big data in this industry. With such input we have compiled information about the main data sources, their uses and data flows, as well as the more noticeable challenges in oil & gas. Overall, the industry is currently transitioning from mere data collection practices to more proactive uses of data, especially in the operations area.

Positive economical externalities associated with the use of big data comprise data generation and data analytics business models, commercial partnerships around data, and the embracement of open data by the Norwegian regulator – the negative ones include concerns with existing business models and reluctance of sharing data by oil companies. In the positive side of social and ethical externalities, safety and environment concerns can be mitigated with big data, personal privacy is not problematic in oil & gas, and there is a need of data scientist jobs; in the negative side, cyber-threats are becoming a serious concern and there are trust issues with data. With respect to legal externalities, regulation of data needs further clarification and ownership of data will be more contract-regulated. Finally, political externalities include the need of harmonize international laws on data and the leadership on big data of some global suppliers.

1 OVERVIEW

The energy case study is focused on the use of big data by the oil & gas upstream industry, i.e. exploration and production activities, in the Norwegian Continental Shelf (NCS). The NCS is rich in hydrocarbons that were first discovered in 1969, while commercial production started in the Ekofisk field in 1971.[79]

The oil & gas industry is technically challenging and economically risky,[80] requiring large projects and high investments in order to extract petroleum. In the case of the NCS, project complexity is further increased since deposits are offshore in harsh waters and climate conditions are challenging. As a result, petroleum activities in the NCS have prioritized long-term R&D and tackled projects that were highly ambitious technically.[81]

Petroleum activities in Norway are separated into policy, regulatory and commercial functions: Norway's policy orientation is focused on maintaining control over the oil sector; the Norwegian Petroleum Directorate[82] (NPD) is the regulator body; while petroleum

[79] Yngvild Tormodsgard (ed.). "Facts 2014 – The Norwegian petroleum sector". The Norwegian Petroleum Directorate. 2014. Available at: https://www.regjeringen.no/globalassets/upload/oed/pdf_filer_2/faktaheftet/fakta2014og/facts_2014_nett_.pdf

[80] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.

[81] Mark C. Thurber and Benedicte Tangen Istad. "Norway's evolving champion: Soil and the politics of state enterprise." Program on Energy and Sustainable Development Working Paper #92 (2010).

[82] http://npd.no/en/

operators compete for oil through a license system. Overall, this separation of concerns is considered the canonical model of good bureaucratic design for a hydrocarbons sector.[83]

1.1 STAKEHOLDERS, INTERVIEWEES AND OTHER INFORMATION SOURCES

There are more than 20,000 companies associated with the petroleum business.[84] Oil operators are large organizations that compete internationally, but also collaborate through joint ventures in order to share project risks. Given the complexity of this industry, there is a multitude of vendors that sell equipment and services through the whole oil & gas value chain: drilling, subsurface and top structure (platform) equipment, power generation and transmission, gas processing, utilities, safety, weather forecasting, etc.

For the realization of this case study we have approached four of the most notable oil operators in the NCS, pseudonomised as Soil, Coil, Loil and Eloin. We have also contacted one of the main vendors in the NCS (codenamed "SUPPLIER" for confidentiality reasons), as well as NPD, the regulator of petroleum activities in Norway. The profiles of these organizations are included in Table 14, according to the categorization of the Stakeholder Taxonomy.[85]

Table 14 Organizations involved in the oil & gas case study

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
Soil	Oil & gas operator	Early majority	Acquisition Analysis Curation Storage Usage	Strategic role
Coil	Oil & gas operator	Early majority	Acquisition Analysis Curation Storage Usage	Strategic role
Loil	Oil & gas operator	Early adopter	Acquisition Analysis Curation Storage Usage	Strategic role
Eloin	Oil & gas operator	Early majority	Acquisition Analysis Curation Storage Usage	Strategic role
SUPPLIER	Oil & gas supplier	Late majority	Analysis Usage	Turnaround role
Norwegian Petroleum Directorate	Oil & gas regulator in Norway	Early adopter	Curation Storage	Factory role

[83] Mark C. Thurber and Benedicte Tangen Istad. "Norway's evolving champion: Soil and the politics of state enterprise." Program on Energy and Sustainable Development Working Paper #92 (2010).
[84] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.
[85] Edward Curry. "Stakeholder Taxonomy". BYTE Project. Deliverable 8.1. 2014.

We have then arranged interviews with senior data analysts and IT engineers from these organizations. The profiles of the interviewees are shown in Table 15 – again, we have followed the classification guidelines included in the Stakeholder Taxonomy.[86] Since Soil is the main facilitator of this case study, we were able to interview [I-ST-1] four times. [I-CP-1] was interviewed twice, while [I-NPD-1] and [I-NPD-2] were both interviewed in two occasions at the same time. We held a single interview with the remaining interviewees. Overall, **we have conducted 11 interviews for this case study**.

Table 15 Interviewees of the oil & gas case study

Code	Organization	Designation	Knowledge	Position	Interest
I-ST-1	Soil	Senior Technical Manager	Very high	Supporter	Very high
I-CP-1	Coil	Data Manager	Very high	Supporter	Very high
I-LU-1	Loil	Technical Manager	Very high	Moderate supporter	High
I-ENI-1	Eloin	Technical Manager	Very high	Moderate supporter	High
I-SUP-1	SUPPLIER	Technical Manager	Very high	Moderate supporter	High
I-NPD-1	Norwegian Petroleum Directorate	Technical Manager	Very high	Moderate supporter	Medium
I-NPD-2	Norwegian Petroleum Directorate	Senior Data Manager	Very high	Moderate supporter	Medium

Besides the interviews, we have held a workshop on big data in oil & gas, as planned in Task 3.3 of the project work plan. The workshop program included two invited talks, a preliminary debriefing of the case study results and a focus group session – see the agenda in Appendix B. We have also assisted to a session on big data in oil & gas that was part of the Subsea Valley 2015 conference.[87] We have used all these events as input for the case study – Table 16 provides an overview of these additional data sources.

Along this report we profusely include statements from the case study sources – especially in the summary tables, but also within the main text – to support our findings. In all cases we employ the codes included in Table 15 and Table 16 to identify the source.

Table 16 Additional data sources in the oil & gas case study

Code	Source	Event	Description
FG	7 industry experts in oil & gas from Soil, an oil well company, Eloin, West / B, V Solutions, and A Solutions, 14 BYTE members	BYTE energy workshop	Focus group on big data in oil & gas

[86] Edward Curry. "Stakeholder Taxonomy". BYTE Project. Deliverable 8.1. 2014.
[87] http://subseavalley.com/nyheter/arkiv/2015/jan/konferanseprogrammet/

IT-ST	Soil	BYTE energy workshop	Invited talk: "Big data in subsea – the operator view"
IT-NOV	An oil well company	BYTE energy workshop	Invited talk: "Big data in subsea – the supplier view"
T-ST	Soil	Subsea Valley Conference 2015 – Parallel session on big data	Talk: "Big data in Soil"
T-McK	A consulting firm	Subsea Valley Conference 2015 – Parallel session on big data	Talk: "Digital Energy"

1.2 ILLUSTRATIVE USER STORIES

In this section we include three user stories that serve to illustrate emerging big data initiatives in the oil & gas industry.

Permanent reservoir monitoring [IT-ST, T-ST]
Soil is deploying myriads of sensors in the sea bottom to monitor reservoirs. For a high-resolution image the microphones need to be in the same place and for this reason they are placed in a permanent basis in the seabed.

Seismic shootings are taken each six months, but it takes months to get the processed data. This data can feed a simulator and the results used to decide to drill a new well, extract more oil and gas, or inject water to keep the pressure up – if the right decisions are taken, recovery rates of the reservoir can be significantly improved.

However, it is possible to do more with the cables and sensors in the seabed. Indeed, Soil is collecting data every second to detect microfractions. This signal is used to decide whether to increase or not the pressure in the reservoir, resulting in better recovery rates. Environmentally this is also good, since Soil can use the sensors to detect oil leakages.

Automated drilling [IT-NOV]
A national oil well company (NOV) aims to automate drilling and by doing this achieve safer, faster and better drilling. Technology-side, they have practically all the pieces in place. With respect to rig systems, all equipment is monitored, e.g. blowout preventers (BOPs), and it is possible to cut the drilling pipe if necessary. NOV has also developed a wired drillpipe with lots of sensors in it that can achieve a significant improvement in drilling speed (a 40% increase with respect to normal drillpipes in their tests). Drilling operations can then be automated, while a human operator only has to set parameters and monitor progress.

Environment surveillance [IT-ST, T-ST]
Soil wants to know if the environment is exposed to unwanted effects when carrying out petroleum activities. The idea of this project is to monitor the seabed before and during operations to assess whether oil extraction activities have an environmental impact, especially in case of nearby big fisheries or corals. With this aim, Soil is deploying mobile and fixed equipment close to the oil & gas plants for capturing video and audio in real time. In case of an emergency, this data can be used to see what is happening and react based on facts.

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

2.1 DATA SOURCES

We have asked our interviewees to describe the data sources employed in exploration, operation and production activities. With their input we have created Table 17 with the most relevant data sources.

Table 17 Main data sources of the oil & gas case study

Data source	Used in	Big data dimensions	Other remarks
Seismic surveys	Scouting Exploration Production	Volume	Confidential
EarthObvslogy models	Exploration Production	Volume	Analytics Confidential
Production data	Production		Confidential
Top-side sensor data	Operations	Volume Velocity Variety	
Subsea sensor data	Operations	Volume Velocity Variety	
In-well sensor data	Operations	Volume Velocity	
Drilling data	Exploration Drilling	Volume Velocity	
Document repositories	Scouting Exploration Operations	Variety	Lifespan
Reference datasets	Scouting Exploration Production		Open

Seismic data is the main source for discovering petroleum deposits. Collecting such data is expensive and typically performed by specialized companies using seismic vessels that send sound waves deep into subsurface and a set of hydrophones to detect reflected waves [I-ST-1]. This process produces significant volumes of data, typically ~100s GB per one raw dataset.[88] Moreover, this is a key asset of oil operators, so security measures are especially enforced in this case.

Seismic surveys are transformed into **3D EarthObvslogy models** – this is probably the most impactful scientific breakthrough of the oil & gas industry.[89] EarthObvslogists and petrophysicists analyse these models to find potential deposits of hydrocarbons. Transforming seismic data into 3D models is computing-intensive and results into further amounts of data, ~1 TB per one processed dataset.[90] Indeed, Soil stores around 6 PB of seismic data (raw and processed) [I-ST-1].

[88] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.
[89] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.
[90] Ibid.

Production data is very important for oil companies and receives a lot of attention. Since this is a commercial-sensitive asset, operators such as Soil do the accounting of production data by themselves. Oil production is measured at every stage of the flow, while the aggregated figures are reported to the partners in the joint venture and also to the Norwegian Government that has a reporting role.

In the last decade, the oil & gas industry has gone into a process of installing **sensors** in every piece of equipment: **top-side, subsea and in-well**. New fields are heavily instrumented, e.g. Edvard Grieg field has approximately 100K data tags [I-LUN-1] and Goliat field has around 80K data tags [I-ENI-1]. Sensors are very diverse and generate a lot of data. Moreover, velocity is also a challenge, e.g. a subsea factory produces 100s of high-speed signals (~10Kbps) and can thus easily generate 1 TB of data per day [I-SUP-1].

Drilling also generates high-volume and high-velocity data. This data is analysed in real time for safety reasons and to monitor the drilling process, i.e. to detect if the reservoir was hit [I-ST-1].

Document repositories are also quite relevant in the oil & gas industry and employed in different stages. For example, post-drill reports can be analysed to obtain the rock types in a well – this can be relevant for other analogue areas under exploration. However, document repositories are typically unstructured and quite varied since a report could be produced anytime since the beginning of oil operations in the NCS (1970s). Therefore, the management of knowledge repositories is quite challenging for petroleum companies [I-ST-1].

Finally, NPD publishes some **reference datasets** as open data – FactPages[91] and Diskos[92] are probably the most relevant ones. FactPages contain information about the activities in the NCS, i.e. licenses, fields, wellbores, discoveries, operators and facilities. The Diskos database includes seismic, well and production data in the NCS.

2.2 DATA USES

With such massive data assets collected in the oil & gas industry, there are a number of uses of data in place, as reflected in Table 18. We describe them in the following paragraphs, organized around the different stages of the upstream value chain.

Table 18 Main uses of data in the oil & gas case study

EXPLORATION & SCOUTING	
Seismic processing	Seismic processing is the classical big data problem in the oil & gas industry [I-ST-1] Seismic data is difficult to analyse, complex EarthObvs-models are employed [I-CP-1] Oil companies have made large investments in expensive infrastructures: clusters and high-performance storage [I-ST-1]

[91] http://factpages.npd.no/factpages/
[92] http://www.npd.no/en/about-us/collaboration-projects/diskos/

	New techniques, methods, analytics and tools can be applied to find new discoveries [I-LU-1]
PRODUCTION	
Reservoir monitoring	Seismic shootings are used to create 3D models of the reservoir in subsurface [I-ST-1] Reservoir simulations are computer intensive and employed to evaluate how much oil should be produced in a well [I-ST-1] A better understanding of reservoirs, e.g. water flowing, can serve to take better decisions in reaction to events [I-CP-1]
Oil exploration	There are also exploration activities in already producing fields to look for oil pockets. This can result in more wells for drilling [I-ST-1]
Accounting of production data	Reporting requirements to the authorities and license partners [I-ST-1, I-NPD-1] Not especially interesting in terms of big data by itself [I-ST-1] Production data can be combined with other data sources, e.g. linking alarms with production data [I-CP-1]
DRILLING & WELLS	
Drilling operations	Drilling data is analysed to minimize the non-productive time [I-CP-1] Operators use drilling data to decide whether to continue drilling or not [I-ST-1]
Well integrity monitoring	Well integrity monitoring is typically done by specialized companies [I-LU-1, I-ST-1] EarthObvslogical models are employed, taking into account the type of rock in the well [I-ST-1]
OPERATIONS	
Condition-based maintenance	Equipment suppliers could make better usage of the data, e.g. to optimize equipment performance. Indeed, there is a strong movement towards condition-based maintenance [I-CP-1] Focus on applying condition-based maintenance [I-SUP-1, I-ST-1, I-LU-1, I-ENI-1, T-ST]
Equipment improvement	We use operational data to improve the efficiency of equipment [I-SUP-1]
Data-driven new products	Some suppliers are using big data to develop new products, e.g. Soil has expensive equipment that can increase the pressure in a reservoir [I-ST-1]
Data-enabled services	Vendors also sell specialized services such as vibration monitoring. For example, SKF is a vendor with expert groups for addressing failures in rotating equipment [I-LU-1] We are interested in selling a service such as system uptime instead of equipment [I-SUP-1] Soil buys services (including data) from the whole supply chain [I-ST-1]
Integrated monitoring centre	Soil has a monitoring centre for the equipment of each vendor supplier. We are considering replacing them with an integrated centre. In this way, it would be possible to get more information from the totality of vendors' equipment [I-ST-1]
Integrated	Big data can be used for making better and faster decisions in operations by

operations	integrating different datasets (drilling, production, etc.) [I-SUP-1] The analytics of integrated data can be very powerful [I-CP-1]

Exploration and scouting

Seismic processing for the discovery of petroleum is the classical big data problem of the oil & gas industry. Operators have made large investments in high-speed parallel computing and storage infrastructures to generate 3D EarthObvslogy models out of seismic data. The resolution of the images obtained with seismic data is low,[93] and for this reason petroleum experts (EarthObvsphysicists and petrophysicists) try to use additional data sources such as rock types in nearby wells and images from other analogue areas [I-ST-1]. Nevertheless, the complexity of exploration data makes the access of data to petroleum experts especially challenging, requiring *ad hoc* querying capabilities. Due to this, the EU-funded Optique project[94] aims to facilitate data access through the use of the Optique platform for a series of case studies, including oil & gas exploration in Soil.[95]

Production

Seismic data is also employed in production for **reservoir monitoring**, creating 3D models of the reservoir in subsurface. Simulations are then carried out to evaluate how much oil should be produced in a well. Nowadays, there is a trend to permanently deploy seismic sensors in the seabed of a reservoir – see the user story on permanent reservoir monitoring in Section 1.2 – allowing the **detection of microseismic activity**. In addition, seismic data from production fields can be employed to **discover oil pockets** that can result in more wells for drilling and thus extend the lifetime of a field. Finally, **production data is carefully accounted** through all stages of the petroleum workflow. Although production data is not especially challenging in terms of big data, it can be combined with other sources to gain further insight, e.g. linking alarms with production data.

Drilling and wells

Drilling operations are normally contracted to specialized companies such as NOV – see stakeholders in section 1.1. Oil operators get the raw data from drillers and then select the target for drilling and decide whether to continue or not, sometimes relying on simulators [I-CP-1]. These decisions are based on the analysis of drilling data, and they aim to minimize the non-productive time of very costly drilling equipment and crews.

Given the complexity of **wells, their integrity is monitored** during their complete lifetime. External companies are contracted for well integrity monitoring, employing EarthObvslogical models and using core samples from the well.

Operations

This is possibly the most interesting area in oil & gas in terms of big data [I-ST-1]. It consists of structured data that is very varied, ranging from 3D models to sensor data. Velocity is also challenging due to the large number of sensors involved producing data in real time. In addition, there are lots of technological opportunities, e.g. Internet of Things. The main

[93] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.

[94] http://optique-project.eu/

[95] Martin Giese, Ahmet Soylu, Guillermo Vega-Gorgojo, Arild Waaler et al. "Optique – Zooming in on big data access." *IEEE Computer*, March 2015, pp. 60-67.

drivers for applying big data here include the reduction of well downtime, improving the lifetime of equipment and reducing the number of staff offshore [I-ST-1].

Among the different uses of data in operations, **condition-based maintenance** is possibly the one that is receiving more attention. Equipment is instrumented to collect data and analytics are then applied for early detection of potential failures before they occur. Condition-based maintenance is thus much more efficient than traditional reactive or calendar-based approaches. Both operators and suppliers are interested in reducing costs and improving the lifetime of equipment; as a result, there are a number of ongoing collaborations to support condition-based maintenance. Vendors are also analysing operational data to **improve the efficiency of equipment**, e.g. using less energy to control the same piece of equipment. The analysis of operational data can also lead to **new data-driven products**, e.g. Åsgard subsea compressor system.[96] Other opportunities in operations include **data-enabled services** such as failure detection or vibration monitoring. **Integrated operations** is another application area that aims to combine data from multiple sources, e.g. operations and production data, and then use analytics to leverage decision-taking processes.

2.3 DATA FLOWS

In this section we analyse the flow of seismic and sensor data, the most notable data sources in the upstream oil & gas industry (see section 2.1). Beginning with seismic data, oil operators normally contract specialized companies such as PGS[97] for conducting seismic surveys. As explained by [I-ST-1], operators are obliged to send the seismic data to the Norwegian government – this is incorporated to NPD's Diskos dataset (also called Petrobank). Seismic data is also shared among the members of a concession joint venture through Diskos. Interestingly, raw data is shared, but not processed data, i.e. EarthObvslogy models. Seismic data is also traded, e.g. in an auction. Other exchanges include the handoff of seismic data to companies such as CGG[98] to detect problems in a reservoir. Since seismic data is a very valuable asset, oil companies take special security measures to conceal it.

Sensor data is captured offshore from the instrumented equipment (subsea, top-side and in-well) and then transferred onshore to a surveillance centre where operations are monitored. However, integrating the data and presenting in an adequate way to human operators is actually a difficult challenge [I-ST-1, I-ENI-1]. [I-CP-1] explains that there are some differences on how the data is captured: sometimes the operator has direct access to sensor data, while in other cases, e.g. drilling, the vendor gets the raw data and sends it to the operator. Oil companies also contract services such as vibration monitoring, providing access to sensor data in these cases [I-LU-1]. Since sensor data is not particularly sensitive, there are more data exchanges among operators and vendors, e.g. for condition-based maintenance of equipment [I-LU-1].

2.4 MAIN TECHNICAL CHALLENGES

We have employed the big data value chain in the Stakeholder taxonomy[99] to structure the technical challenges in the oil & gas industry:

[96] http://www.akersolutions.com/en/Global-menu/Media/Feature-stories/Subsea-technologies-and-services/Asgard-subsea-gas-compression-system/
[97] http://www.pgs.com/
[98] http://www.cggveritas.com
[99] Edward Curry. "Stakeholder Taxonomy". BYTE Project. Deliverable 8.1. 2014.

- **Data acquisition**: seismic surveys are expensive to take and require months to get the results [I-ST-1, IT-ST]. In contrast, sensor data is easier to acquire and the trend is to increase the number of sensors in equipment, getting more data and in a more frequent basis [I-ST-1].
- **Data analysis**: seismic processing is computing-intensive, as discussed in section 2.2. Another concern is that the oil & gas industry normally do analytics with small datasets [I-CP-1].
- **Data curation**: IT infrastructures in oil & gas are very siloed, and data aggregation is not common [I-ST-1]. In this regard, [I-CP-1] advocates data integration to do analytics across datasets, while [T-McK] proposes to arrange industry partnerships to aggregate data.
- **Data storage**: the oil & gas industry is in general good at capturing and storing data [I-CP-1]. However, [T-McK] claimed that 40% of all operations data was never stored in an oil plant case study.
- **Data usage**: section 2.2 extensively describes the main uses of data in exploration and production activities, demonstrating the value of data in the oil & gas industry. Nevertheless, there is potential to do much more, according to the majority of our data sources. For instance, [T-McK] reported that, based on an oil plant case study, 99% of all data is lost before it reaches operational decision makers.

2.5 BIG DATA ASSESSMENT

In our fieldwork we have collected a number of testimonials, impressions and opinions about the adoption and challenges of big data in the oil & gas industry. With this input we have elaborated Table 19, containing the main insights and the statements that support them.

Table 19 Assessment of big data in the oil & gas case study

Insight	Statement [source]
Big data in oil & gas is in the early-middle stages of development	Big data is still an emerging field and it has not yet changed the game in the oil & gas industry. This industry is a late adopter of big data [I-CP-1] Everybody is talking about big data, but this industry is fooling around and doing small data [T-McK] Big data is quite new for SUP [I-SUP-1] This industry is good at storing data, but not so much at making use out of it [I-CP-1] Oil and gas is still at the first stage of big data in the sense that it is being used externally but not to acquire knowledge for themselves. For example, lots of data about what happens when the drill gets stuck, but they are not using that data to predict the drill getting stuck. Structured data plus interpretation/models are not being converted into knowledge [FG] There are a lot of areas that can be helped by big data. How can we plan when to have a boat coming with a new set of pipes? [FG] Machine learning is beginning to be integrated into technical systems [FG]
More data available in oil & gas	In exploration, more sensors are employed, and microphones for collecting seismic data are permanently deployed at the seabed in some cases [I-ST-1]

	Coil has hundreds of TBs from the Ekofisk area. Volume is an issue, since seismic datasets are growing [I-CP-1] PRM (Permanent Reservoir Monitoring) will push volume of seismic data from the Terabyte to the Petabyte region, due to more frequent data collection [I-CP-1] Soil has 8PB of data and 6PB are seismic. Seismic data are not structured and are stored in files [I-ST-1] The volume of sensor data is big (TBs and increasing), with little metadata [I-ST-1]
Variety and velocity are also important challenges	Operations data is very varied, ranging from 3D models to sensor data, and velocity is also a challenge [I-ST-1] Any piece of equipment is identified with a tag, e.g. pipes, sensors, transmitters. On Edvard Grieg field there are approx. 100.000 tags. Eloin has 10K unique instruments, each collecting approx. 30 different parameters on the average [I-LU-1] Scouting for hydrocarbons involves a huge analytical work in which the main challenges are volume, quality and, especially, variety [I-ST-1] A subsea factory is a very advanced equipment consisting of several connected processing components. It can generate 100s of high-speed signals (~10Kbps). Thus, it can easily generate 1 TB of data per day. It will typically use optical fibre connection with high bandwidth [I-SUP-1]
Data overflow and visualization of data	In the Macondo blowout in 2010 there was so much data that operators could not take an action in time. As humans we cannot deal with all the data [IT-NOV] In operations the visualization of data is not sufficiently effective and comprehensible. Something is missing with respect to the user, even if you have a monitor, you need to interpret what is presented and the interconnections of data are not evident [I-ENI-1] There are lots of data coming in from different components. A challenge for the operator is how to pay attention to/align the information coming in on 15 different screens. How to simplify this into manageable outputs? [FG]
Analytics with physical models VS data-driven models	An important question is how to do analytics. One classical way is to employ physical models. Another path is just looking for correlations [I-CP-1] We normally employ physical models, while another possibility is the use of data-driven models – although their value has to be proven here. Soil is currently trying different models with the available data [I-ST-1] In some sectors there is the idea that you should "let the data speak for itself" but in the more classical oil and gas approach, you will base the analytical models on equations and models (physics) [FG] We have tested the distinction between the physical models and the machine learning models. Two years ago, the physical models performed better, but the machine learning models are constantly evolving [FG]
Resistance to change	A lot of the technology is there, but the mindset is the main problem [IT-

	NOV] It is extremely difficult to change the drilling ecosystem because of the different players involved – many of them are reluctant to introduce changes [I-ST-1] There are many possibilities to reduce production losses by analysing the data, but the business side is not ready yet to look into this [I-CP-1]
Effectiveness of big data in oil & gas	Everybody is trying to do big data, but the industry needs success stories to know what can be really done with big data. Right now, it is not easy to foresee what can be done; there are some analytics and time series analysis under way, but next level is to get real knowledge out of the data [I-SUP-1] Big data analytics introduces uncertainty, but we don't have so much experience with big data so as to report concerns [I-CP-1] It costs something to analyse 2000 data points, and you have to have a good reason to invest in that analysis [FG]

Our assessment reveals that the oil & gas industry is **beginning to adopt big data**: stakeholders are collecting as much data as possible, although there is some criticism about its actual usage in practice – this suggests an awareness of the potential of big data in oil & gas.

While this industry is quite familiar to **high volumes of data**, we can expect exponential growths in the near future, as new devices to track equipment and personnel performance are deployed everywhere and collecting more data than ever. Nevertheless, volume is not the only data challenge that the oil & gas industry is facing; **variety and velocity are becoming increasingly important** as more data signals are combined and analysed in real-time. Moreover, **humans cannot deal with such amounts of data, requiring effective tools for visualizing, querying and summarizing data**.

Big data advocates propose to find correlations and patterns in the data, without requiring a preliminary hypothesis – this is sometimes referenced as "let the data speak".[100] In contrast, the oil & gas industry relies on well-established physical models for doing analytics. This **disjunctive between physical and data-driven models** is currently under discussion in this domain.

Still, there is some **resistance to embrace big data practices and techniques** in oil & gas. In many cases the technology is already available, but decision-takers are somewhat reluctant to introduce changes – especially if business models are affected. Nonetheless, the **effectiveness of big data has to be proved** in oil & gas, and the industry needs success stories that showcase the benefits that can be reaped.

3 ANALYSIS OF SOCIETAL EXTERNALITIES

3.1 ECONOMICAL EXTERNALITIES

[100] Viktor Mayer-Schönberger and Kenneth Cukier. *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt, 2013.

We include in Table 20 the economical externalities that we have found in the oil & gas case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 20 Economical externalities in the oil & gas case study

Code	Statement [source]	Finding
E-OO-BM-2	There are specialized companies, like PGS, that perform seismic shootings [I-ST-1] Soil hires other companies for seismic shootings [I-ST-1]	Data generation business model
E-OO-BM-2	There is a company from Trondheim that has created a database of well-related data (Exprosoft). This company is specialized in projects of well integrity. They gather data from a well and then compare it with their historical dataset using some statistics [I-LU-1] Wells are more complex and are monitored during their complete lifetime. Well data is processed by an external company [I-ST-1]	Data analytics business model
E-OO-BM-3	Who's paying for the technology? It is necessary to find the business case, since technology-side is possible. The biggest challenge is the business model [IT-NOV] Drilling is a funny business; there are no incentives to drill faster [IT-NOV] There are also economical challenges; we do not have a positive business case for deploying data analytics [FG] How can machine learning companies be players, given the complexity of the oil and gas industry? How can that happen and what will be the effects if that happens? [FG]	Not clear data-based business models
E-OO-BM-1	Condition-based maintenance is an example of an ongoing collaboration with our clients [I-SUP-1] We have an agreement of 2 years for collaborating with vendors. They will collect data and learn from it, before migrating to condition-based maintenance [I-ENI-1] We are running pilots for condition-based maintenance; sometimes we do these pilots alone, and other times in collaboration with suppliers. As a result, we have now some equipment in production [I-ST-1]	Commercial partnerships around data
E-OO-BM-1	Data-enabled services can be commercialized on top of the equipment sold in order to provide improved services to the clients [I-SUP-1] Some suppliers want to sell services, not just equipment. This is because they earn more money with services and because they have the experts of the machinery [I-ST-1] As the manufacturers, suppliers are in the best position to analyse operational data [I-SUP-1] Suppliers are typically constrained to one "silo", so they are not	Suppliers are trying to sell data-based services

	generally capable of working with big data. Even suppliers like General Electrics (which are good in big data) are limited due to this problem. In contrast, oil companies like Coil can provide a holistic view of operations, so they are more naturally capable of doing big data in this area [I-CP-1]	
E-PO-BM-1	Norway aims to attract investors to compete in the petroleum industry. The FactPages constitutes an easy way to assess available opportunities in the NCS by making openly available production figures, discoveries and licenses [I-NCS-2] NPD began in 1998-1999 to publish open data of the NCS. This is a fantastic way to expose their data and make it available to all interested parties. Before that, companies directly asked NPD for data. NPD has always promoted the openness of data and resources. In this regard, NPD pursues to get as much as possible of the data [I-NCS-1] Companies are also obliged to send the seismic data to the Government – this is incorporated to NPD's Petrobank, i.e. the Diskos database [I-ST-1]	Open data as a driver for competition
E-OO-BM-2	Soil is reluctant to share data in exploration, but we have more incentives to share data in operations [I-ST-1] It could be risky to have access to all the operational data. Exposing commercial sensitive information is a concern for both petroleum operators (in terms of fiscal measures), and for suppliers in terms of equipment and service performance [I-SUP-1] Some oil operators do not share any data. However, there is an internal debate among operators about this position, and opening data is proposed to exploit added-value services [I-SUP-1] Operations data is not secret or confidential. We are not very protective as a community [I-LU-1] Since it is the operator's interest to give access to data to vendors, this is not an issue and access to data is granted [I-LU-1] There is a problem with different players (driller, operator, reservoir monitor) in the same place, but not sharing anything. How to integrate data that drillers do not have? [IT-NOV]	Companies are somewhat reluctant to open data, but there are emerging initiatives

With the advent of big data in oil & gas, new business models based on data have appeared. One of them is based on **data generation**, and we can find companies like PGS that are contracted by petroleum operators to perform seismic shootings. Moreover, datasets such as seismic surveys are traded in all stages of the oil & gas value chain. **The data analytics business model** is also getting traction: analytics are employed to improve equipment efficiency; some companies are selling specialized services such as well integrity or vibration monitoring; and new products based on data analytics are introduced to the market, e.g. Åsgard compressors.

However, **there are some challenges with the business models**, requiring funds for investments or other incentives in order to introduce already available new technologies – see

for instance the automated drilling user story in Section 1.2. In this regard, there are some incipient **commercial partnerships around data**. For example, petroleum operators and suppliers typically collaborate to apply condition-based maintenance to equipment. Moreover, surveillance centres for monitoring equipment require collaboration among field operators and suppliers – see integrated monitoring centre in Table 18.

Given that everybody is realizing the value of data, **suppliers are trying to sell data-based services**, not just equipment. Since access to data is contract-dependent, this situation creates some tensions. On the one hand, suppliers are in the best position to analyse operational data since they are the manufacturers of the equipment. On the other hand, suppliers are typically constrained to one domain ("silo"), while oil companies are in a better position to provide a holistic view of operations.

NPD, the regulator of petroleum activities in Norway, plays a key role in facilitating the access to oil & gas data. In this regard, NPD closely collaborates with the industry to gather data about petroleum activities in the NCS. This way, **NPD aims to promote competition among petroleum operators, embracing open data to facilitate access**. This is especially important for small companies since collecting data is extremely difficult and expensive. Moreover, reporting obligations benefit the petroleum industry as a whole, avoiding companies to duplicate efforts on data collecting activities.

Companies are also considering **open data as an opportunity for commercial benefit**. Specifically, operators have many incentives to share operations data since privacy concerns are low and there are many opportunities to obtain efficiency gains in operations. However, operators are reluctant to share data in exploration, since it is possible that other parties discover oil deposits. With respect to suppliers, they would prefer to keep the data for themselves, but this is not always possible since data normally belongs to the owner of the equipment (depending on the terms and conditions of the contract). As a result, there are ongoing open data pilots and sharing data collaborations, especially with operations data.

3.2 SOCIAL & ETHICAL EXTERNALITIES

We include in Table 21 the societal & ethical externalities that we have found in the oil & gas case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 21 Social & ethical externalities in the oil & gas case study

Code	Statement [source]	Finding
E-OC-BM-3	There are changes in hiring practices, requiring employees with the competences to use the data [FG] There are very few data scientists at Coil. We need more [I-CP-1] Data scientists are not getting into the oil & gas industry. Make a business case and then hire data scientists [T-McK]	Need for data analyst jobs
E-OC-ETH-10	We use industrial data, not Twitter [IT-ST] With big data it could be possible to find who made a bad decision, e.g. a human operator [I-SUP-1]	Personal privacy is not a big concern
E-OO-DAT-3	Opening up entails some risks. For instance, it could maybe be possible to extract sensitive data such as the daily production of a	Cyber-attacks and threats to

	field [I-SUP-1] Security/hacking is very much an issue for NPD. Oil & gas information is very important and NPD has a great responsibility. Indeed, companies have to keep trust on NPD. Thus, NPD takes many protective measures such as firewalls and security routines [I-NPD-1] Coil has lots of attacks from outside, although we have taken many security measures in IT. Indeed, NPD has instructed oil companies to take measures in this respect [I-CP-1] The O&G industry is exposed to cyber-threats. Some companies have received serious attacks; protection measures are needed! [IT-ST]	secret and confidential datasets
E-OC-ETH-1	Big data can help to reduce incidents, e.g. the detection of oil leakages. DTS data can also improve safety when employed for reservoir monitoring [I-CP-1] Big data helps to give a clear picture of the field operation, and it facilitates the detection of oil leakages or equipment damage [I-SUP-1] The control system has a lot of alarms and it is literally impossible to manually analyse them all. As an alternative, we can trust the software to automatically analyse them [I-CP-1] I do not see changes due to big data in safety [I-LU-1] Do we expose the environment for unwanted effects? Soil wants to know and to show that we don't. We use cameras and sound recorders in the sea (close to the O&G plants), especially if there are big fisheries or corals nearby. We want to see if something bad is happening [IT-ST] We are beginning to monitor the seabed before operations. With this data, Soil can act faster if something is going wrong. We have mobile & fixed equipment capturing video and audio in real time. It can be employed in case of emergency and this data can be shared with others [T-ST]	Big data can help to improve safety and environment
E-OO-DAT-4	The data ecosystem is complex, and there are many communication exchanges between oil companies and suppliers – I think that nobody can give a complete overview of the data exchanges in place [I-CP-1] It is difficult to trust information coming out of the data if you do not have a clear relationship to the underlying reality and if it is not generated by your organisation [FG] Those who produce the data only give away aggregated data, and a selection of that aggregated data to specific users. If you want to trust the information that the system gives you, it can verify that the system is doing what it is supposed to [FG]	Issues on trusting data coming from uncontrolled sources

There is a gap between data scientists and technical petroleum professionals that has not been bridged yet.[101] Nevertheless, **the oil & gas industry is becoming interested in hiring data analysts** to exploit the potential of big data for the integration of large data volumes, to reduce operating costs and improve recovery rates and to better support decision management.

In this domain, **personal privacy is not a big concern** and there is little value of social media. Nevertheless, it could be possible to find human errors by analysing operations data. In contrast, some datasets are highly secret and confidential, so **cyber-security measures are quite important** and have been adopted through the whole industry – NPD provides guidelines for securing IT infrastructures.

Traditionally, safety and environment concerns have been pivotal for petroleum activities in the NCS and there are high standards to comply with safety and environment requirements. **Big data can help to reduce environmental impacts** by the early detections of incidents, e.g. oil leakages, and by improving equipment efficiency, e.g. through condition-based maintenance. There are also pilot initiatives – see the environment surveillance user story in Section 1.2 – that can be highly valuable to assess the impact of oil extraction activities and to act faster in case of an accident.

There is also a **trust issue with data coming from uncontrolled sources**. This is especially relevant when aggregating data or when applying data-driven models.

3.3 LEGAL EXTERNALITIES

We include in Table 22 the legal externalities that we have found in the oil & gas case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 22 Legal externalities in the oil & gas case study

Code	Statement [source]	Finding
E-PO-LEG-1	NPD has an important regulation role in the petroleum industry. Existing regulation is the result of many years working very closely with operators. They have held many discussions upfront to facilitate this process. Moreover, NPD tries to not ask too much from companies. As a result, companies do not complain about existing regulation [I-NPD-1] A license can include the seismic data that is shared by every partner in the joint venture. Indeed, this is highly regulated in the joint venture [I-ST-1]	Mature oil & gas regulation in Norway
E-PO-LEG-1	The ownership of operation data is dependent on the contract. Sometimes Soil can get less data than is captured, while more data could go to suppliers. This applies to well drilling data and to the machinery on top of a field. This is a complicated ecosystem [I-ST-1] Legislation of data is still unclear [I-SUP-1]	Regulation of big data needs clarification

[101] Adam Farris. "How big data is changing the oil & gas industry." *Analytics Magazine*, November/December 2012, pp. 20-27.

	There is no clear thinking about the regulations with respect to big data yet, and these must be clarified in order to deal with issues around liability, etc. [FG] Making raw data regulated is something that has to be judged on the criticality of the risk. Ideas like black boxes could carry over into this industry because the risks of malfunction can be so severe [FG]	
E-PO-LEG-1	Data ownership is regulated by the terms and conditions – the owner of the equipment is commonly the owner of the data [I-LU-1] Data will be more contract-regulated [FG] Data ownership is also a key issue. Those who produce the data only give away aggregated data, and a selection of that aggregated data to specific users [FG]	Data ownership is key and will be heavily regulated

Petroleum activities in Norway rely on a **mature regulation framework that enforces the separation of policy, regulatory and commercial functions**. The Petroleum Act[102] provides the general legal basis for the licensing that governs Norwegian petroleum activities. This is the result of many years of close collaboration of NPD with field operators. These have reporting obligations for seismic and production data, but receive support on legislation about safety, licensing and other issues. As a result, all players have trust in NPD and accept their obligations in the petroleum industry.

While production and seismic data are highly regulated by the authorities, other datasets, e.g. operations data, are normally regulated by the terms and conditions of a contract. In this regard, the owner of data is normally the owner of the equipment that produces the data. There are some exceptions, though – for instance, drilling companies normally collect the raw data that is then supplied to operators. Therefore, **legislation of big data aspects requires additional clarification**. Indeed, industry stakeholders are becoming increasingly aware of the value of data, so **ownership of data will possibly be subject of contention**.

3.4 POLITICAL EXTERNALITIES

We include in Table 23 the political externalities that we have found in the oil & gas case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 23 Political externalities in the oil & gas case study

Code	Statement [source]	Finding
E-OO-DAT-2	Data availability is an issue in international projects in which Soil does not know much about the EarthObvslogy. In these cases, we try to buy data from other companies that have a strong presence in the surrounding area [I-ST-1]	Data is a valuable asset traded internationally
E-PP-LEG-2	There is a lot of legislation to take care of. Legislation is different for each country, but there are some commonalities. For example, the data has to be kept at the country of origin,	Need to harmonize international

[102] Act No. 72 of 29 November 1996 relating to petroleum activities.

	although it is commonly allowed to copy data [I-ST-1]	legislation w.r.t. data
E-OO-BM-5	Some of the main suppliers, […], have become big data experts [I-ST-1]	Some suppliers are becoming leaders in big data

Since the oil & gas industry requires high investments, operators and suppliers are normally international organizations with businesses in many countries. Oil operators purchase data (especially seismic) from other companies with a strong presence in the surrounding areas in order to carry out exploration and scouting activities. **Data is thus becoming a valuable asset that is traded internationally**.

International legislation is problematic for oil companies, since different laws apply to each country. Nevertheless there are some commonalities; seismic data has to be kept at the country of origin, although oil operators are normally allowed to make a copy of the data.

Finally, **some of the main petroleum suppliers, […], have become big data experts** and are thus especially interested in selling data services, not just equipment.

4 CONCLUSION

The oil & gas domain is transitioning to a data-centric industry. There is plenty of data, especially due to the deployment of sensors everywhere, but also many technical challenges to undertake. Some of the most striking ones include data analytics, data integration and data visualization. While big data still needs to prove its effectiveness in oil & gas, the industry is beginning to realize its potential and there are many ongoing initiatives, especially in operations. With the current oil price crisis, big data is an opportunity to reduce operational costs, to improve the extraction rates of reservoirs – through optimized decision-taking processes – and even to find more oil in exploration activities.

In our case study we have identified a number of economical externalities associated with the use of big data in oil & gas: data generation and data analytics business models are beginning to get traction, there is a number of commercial partnerships around data and the Norwegian regulator has embraced open data in order to spur competition among oil operators. However, companies are still reluctant to share their data, despite some emerging initiatives. Moreover, existing business models have to be reworked in order to promote the adoption of big data.

In the positive side of social and ethical externalities, safety and environment concerns can be mitigated with big data, personal privacy is not problematic in oil & gas and there is a need of data scientist jobs – though operators and other types of jobs might be less demanded. On the negative side, cyber-security is becoming a serious concern and there are trust issues with third-party data and data-driven analytics.

The petroleum industry benefits from a mature regulation framework in Norway, although regulation of data requires further clarification. Moreover, companies are increasingly aware of the value of data and we can expect contention about data ownership. Many companies in the oil business are multinationals, so there is a need to harmonize international legislation with respect to data. Indeed, some vendors are becoming leaders in big data, and the rest should embrace big data in order to succeed in the future.

ENVIRONMENT CASE STUDY REPORT - *FOR SOUND SCIENCE TO SHAPE SOUND POLICY*

SUMMARY OF THE CASE STUDY

The environment case study has been conducted in the context of an earth observation data portal (EarthObvs), a global-scale initiative for better understanding and controlling the environment, to benefit Society through better-informed decision-making. This has given us an excellent test bed for investigating the societal externalities of Big Data in the environment sector.

We have interviewed six senior data scientists and IT engineers in the EarthObvs community, as well as in the modelling and the meteorological communities. We have also conducted a focus group with environment experts and attended a workshop targeted at EarthObvs Science and Technology stakeholders. With such input we have compiled information about the main data sources, their uses and data flows, as well as the more noticeable challenges in the environment.

The authoritative EarthObvs and a Space Observation portal SPObvs) are the typical sources of data (mainly from remote sensing), however there is a growing interest in non-authoritative data, such as crowdsourcing, and in synthetic data from model outputs. Myriads of applications make use of environmental data, and data flows may be virtually unconstrained, from the producers to the consumers, passing by multiple independent processors. Institutional arrangements and policies are the fundamental regulatory aspect of environmental data exchange. These can range from application-specific Service Level Agreement, to overarching policies, such as the EarthObvs Data Sharing Principles. The main challenges reported include data access, and Open Access policies are considered effective also to mitigate other technical issues. In general, there is a perception that technical challenges are easy to overcome and that policy-related issues (above all, data quality) are the real hindrance to Big Data in the environment sector.

Positive economical externalities associated with the use of big data in the environment include economic growth and better governance of environmental challenges – the negative ones comprise the possibility of putting the private sector (and especially big players) to a competitive advantage. On the positive side of social and ethical externalities, data-intensive applications may increase awareness and participation; on the negative side, big-brother-effect and manipulation, real or perceived, can be problematic. With respect to legal externalities, regulation needs clarification, e.g. on IPR. Finally, political externalities include the risk of depending on external sources, particularly big players, as well as EarthObvs political tensions.

1 OVERVIEW

The environment, including the Earth's atmosphere, oceans and landscapes, is changing rapidly, also due to the increasing impact of human activities. Monitoring and modelling environmental changes is critical for enabling governments, the private sector and civil society to take informed decisions about climate, energy, food security, and other challenges. Decision makers must have access to the information they need, in a format they can use, and in a timely manner. Today, the Earth is being monitored by land, sea, air and Space.

However, the systems used for collecting, storing, analysing and sharing the data remain fragmented, incomplete, or redundant.

The BYTE case study in the environment sector has centred on an Earth Observation Development Board (EODB) of a group on Earth Observation (EarthObvs). We have sought the assistance of EarthObvs-EODB in identifying the potential externalities that will arise due to the use of Big Data in the environment sector. To this end, we were interested in scoping the possible implications of environmental data-intensive applications on Society.

The methodology used to conduct the case study derives from the generic BYTE case study methodology,[103] based on:

- Semi-structured interviews;
- Document review;
- Disciplinary focus groups.

1.1 STAKEHOLDERS, INTERVIEWEES AND OTHER INFORMATION SOURCES

With over 90 members and a broadening scope, EarthObvs is not just specific to Earth Observation, but is evolving into a global venue to support Science-informed decision-making in nine environmental fields of interest, termed Societal Benefit Areas (SBAs), which include Agriculture, Biodiversity, Climate, Disasters, Ecosystems, Energy, Health, Water, and Weather. Furthermore, EarthObvs is in an important item in the EC agenda.

For a decade now, EarthObvs has been driving the interoperability of many thousands of individual space-based, airborne and in situ Earth observations around the world. Often these separate systems yield just snapshot assessments, leading to critical gaps in scientific understanding.

To address such gaps, EarthObvs is coordinating the realization of a universal earth observation system (EOSystem), a global and flexible network of content providers providing easy, open access to an extraordinary range of data and information that enable an increasingly integrated view of our changing Earth. From developed and developing nations battling drought and disease, to emergency managers making evacuation decisions, farmers making planting choices, companies evaluating energy costs, and coastal communities concerned about sea-level rise, leaders and other decision-makers require this fuller picture as an indispensable foundation of sound decision-making.

The first phase of EOSystem, implementation will end in 2015. A new work plan for the second phase (2016-2025) is under definition. EOSystem already interconnects more than thirty autonomous infrastructures, and allows discovering and accessing more than 70 million of extremely heterogeneous environmental datasets. As such, EOSystem had and has to face several challenges related to Big Data.

The EarthObvs-EODB is responsible for monitoring progress and providing coordination and advice for the five Institutions and Development Tasks in the EarthObvs 2012-2015 Work Plan. These five Tasks address "EarthObvs at work" and the community's efforts to ensure that EOSystem is sustainable, relevant and widely used; they focus on reinforcing data sharing, resource mobilization, capacity development, user engagement and science and

[103] Guillermo Vega-Gorgojo, Grunde Løvoll, Thomas Mestl, Anna Donovan, and Rachel Finn, *Case study methodology*, BYTE Deliverable D3.1, BYTE Consortium, 30 September 2014.

technology integration. The Board is composed of around 20 members and includes experts from related areas. A partial list of EarthObvs-EODB stakeholders is shown in Table 24, according to the categorization of the BYTE Stakeholder Taxonomy.[104] Note that private sector organisations participate in EarthObvs as part of their respective national membership [WS].

Table 24 – Organizations involved in the environment case study

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
EC	Public Sector (EU)	Early majority	Usage	Support role
EEA	Public Sector (EU)	Early majority	Analysis Curation Usage	Factory role
EPA	Public Sector (USA)	Early majority	Analysis Curation Usage	Factory role
EuroEarthObvsSurveys	Public Sector (EU)	Late Majority	Acquisition Analysis Curation Usage	Factory role
EUSatCen	Public Sector (EU)	Early Adopters	Acquisition Analysis Curation Storage Usage	Strategic role
IEEE	Professional association	Innovators	Acquisition Analysis Curation Storage Usage	Strategic role
NASA	Space (USA)	Innovators	Acquisition Analysis Curation Storage	Strategic role
SANSA	Space (South Africa)	Innovators	Acquisition Analysis Curation Storage	Strategic role
UNEP	Public Sector	Late majority	Analysis Curation Storage Usage	Turnaround role

We have tailored the questions of the semi-structured interview proposed in the methodology to the EarthObvs community, and arranged interviews with the leaders of the EarthObvs-OEDB tasks, compatibly with their availability, as well as the more general point of view of the EarthObvs Secretariat, interviewing a senior officer (seconded by a major space agency). We also sought to capture the viewpoints of a senior data manager from the climate/Earth

[104] Edward Curry, Andre Freitas, Guillermo Vega-Gorgojo, Lorenzo Bigagli, Grunde Løvoll, Rachel Finn, *Stakeholder Taxonomy*, BYTE Deliverable D8.1, BYTE Consortium, 2 April 2015.

System modelling community, possibly the most data-intensive application in the environment sector, insofar not particularly involved in EOSystem; and that of a senior professional meteorologist, responsible for 24/7 operational production of safety critical products and emergency response activities. The profiles of the interviewees are shown in Table 25 – again, we have followed the classification guidelines in the Stakeholder Taxonomy.[105] The "Organization" column indicates the main affiliations of the interviewees. Note that I-2 has responded both as a member of the Academic Science & Technology community and as a C-level executive of a Small and Medium Enterprise.

Table 25 – Interviewees of the environment case study

Code	Organization	Designation	Knowledge	Position	Interest
I-1	EarthObvs-OEDB/UNEP	Scientist	High	Moderate Supporter	Average
I-2	EarthObvs-OEDB/IEEE/ private SME	Senior scientist/ CEO	Very high	Supporter	Very high
I-3	EarthObvs-OEDB/private SME	CEO	High	Supporter	Very high
I-4	EarthObvs/JAXA	Senior officer	Very high	Supporter	Very high
I-5	DKRZ	Data manager	Low	Moderate Supporter	Average
I-6	Met Office	IT Fellow	Average	Moderate Supporter	Average

Besides the interviews, we have resorted to additional data sources to integrate the case-study research. Thanks to a favourable timing, we have taken the opportunity to complement our interviews with first-hand input from the EOSystem Science & Technology community, by participating in the 4th EOSystem S&T Stakeholder Workshop, held on March 24-26 in Norfolk (VA), USA. Besides, as per the BYTE case study methodology,[106] we have held a focus group meeting on April 13th, in Vienna. This event was co-located with the European EarthObvssciences Union General Assembly Meeting 2015,[107] with the aim of more easily attracting experts and practitioners on Big Data in the environment sector. Table 26 provides an overview of such additional data sources.

Table 26 – Additional data sources in the environment case study

Code	Source	Event	Description
WS	8 EOSystem S&T stakeholders, including SANSA, IEEE, APEC Climate Center, Afriterra Foundation, CIESIN; 1 BYTE member	4th EOSystem Science and Technology Stakeholder Workshop, 24-26 March, Norfolk (VA), USA	The organization has offered us the opportunity to chair and tailor one of the sessions on emerging revolutions challenges and opportunities (i.e. Breakout Session 1.1: Cloud and Big Data Revolutions, on Wednesday 25 March) to

[105] Edward Curry, Andre Freitas, Guillermo Vega-Gorgojo, Lorenzo Bigagli, Grunde Løvoll, Rachel Finn, *Stakeholder Taxonomy*, BYTE Deliverable D8.1, BYTE Consortium, 2 April 2015.
[106] Guillermo Vega-Gorgojo, Grunde Løvoll, Thomas Mestl, Anna Donovan, and Rachel Finn, *Case study methodology*, BYTE Deliverable D3.1, BYTE Consortium, 30 September 2014.
[107] http://www.egu2015.eu/

			BYTE needs
FG	6 experts from academia, research, industry in environment and EarthObvsspatial sector, including GSDI, JAXA, ESA, AIT; 5 BYTE members	BYTE Focus Group Meeting, 13 April 2015, Vienna (Austria)	Focus group meeting on Big Data in the environment sector

The 4th EOSystem S&T Stakeholder Workshop was promoted by IDIB task ID-03:

Advance EOSystem through integration of innovations in Earth observation science and technology, also enabling the research community to fully benefit from EOSystem accomplishments. Promote research and development (R&D) in key areas of Earth sciences to facilitate improvements to Earth observation and information systems, and support the transition of systems and techniques from research to operations. Engage with a wide range of science and technology communities including individual scientists and their institutions, both public and private.

Participants included technology developers; experts in data management, integration, and analysis; developers of knowledge systems and concepts for the linkage between decision-making and knowledge; and user representatives. The workshop has focused, among others, on the rapid development in (big) data availability, not only from traditional sensors but also from a variety of human sensors, the developing Internet of Things (IoT) and Internet of Everything (IoE) scenarios, and the output of increasingly more advanced models. The outcomes of the workshop include position papers on various aspects of the future EOSystem, including the handling of the emerging "data super nova".

The disciplinary focus group meeting had the purpose to gain greater insight into the data, technologies, applications and potential positive and negative impacts that may result from the use of Big Data in the environmental sector. Focus group participants have been selected to ensure the participation of individuals with expertise in environmental data, technology, computer science, EarthObvsspatial standardisation, the space sector, as well as privacy and data protection, open data policies, relevant policy issues such as funding and innovation. The focus group meeting agenda is reported in Appendix C and included a debriefing on BYTE preliminary results and two sessions of discussion in three small groups, reporting to the overall attendance.

Along this report we profusely include statements from the case study sources – especially in the summary tables, but also within the main text – to support our findings. In all cases we employ the codes included in Table 25 and Table 26 to identify the source.

1.2 ILLUSTRATIVE USER STORIES

Damage assessment in buildings [FG]
In urban environments, remote sensing allow monitoring fine displacement of buildings, due to subsidence, shrinking, etc. High-resolution satellite data, especially when coupled with Building Information Models help assessing potential vulnerabilities and prevent damages before they actually happen. This is also a typical use case in emergency response situations, such as post-earthquake damage assessment, etc.

Renewable energy forecast [FG]
Specific sensors and algorithms allow estimating the amount of snow cover on a given mountain area; this information can be fed into hydrological and climatological models, which can compute an estimation of the melting process, and the resulting water flow, for example in a particular river basin, which in turn can be chained to other model, to support forecasting the power that will be produced in the future by a hydropower plant, and made available to a community.

Drug traffic monitoring [FG]
In a real-world use case, ESA cooperated with the US Administration to fight drug traffic from Mexico to the North-American coasts. Drug cartels used powerful off-shore boats running at full speed in the Gulf of Mexico, to smuggle drug and other illegal material. Given the extension of the potential crime scene and the technical characteristics of the boats in use, it was very difficult for the police authorities to effectively patrol and repress such activities. Thanks to high-resolution Earth Observation (EO) data, and to appropriate image recognition processes calibrated to spot the typical pattern created by a high-speed off-shore boat in the sea waves, a space observation portal was able to help deploying and directing the available resources more effectively (unfortunately, maybe also as a consequence of this success story, the cartels have been known for a while to utilize submarines).

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

Part of our field work has aimed at investigating the main processes of interest in the environment use-case, elucidating their inputs in terms of data sources, acting parties, and policies (see Figure 1). This chapter reorganize the material according to the activities of the BYTE Big Data Value Chain[108], and highlights the main related technical challenges.

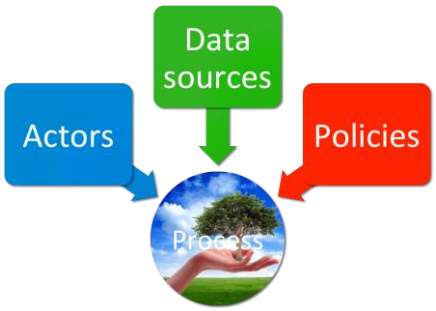


Figure 1 – Input model of a process in the environment use-case

2.1 DATA SOURCES

The main data sources identified by our case-study participants during our fieldwork are summarized in Table 27.

Table 27 – Main data sources of the environment case study

Data source	Used in	Big data dimensions	Other remarks

[108] Edward Curry, et al. Op. Cit., p. 18.

Space component (satellite data, etc.)	Modelling Information extraction Analysis	Volume Velocity Variety Value	Cf. Copernicus[109] and the ESA Big Data from Space initiative[110]
In-situ component (rain gauges, buoys, etc.)	Modelling Information extraction Analysis	Volume Velocity Variety Value	Openness still unsolved [FG]
Service component (models, etc.)	Modelling Information extraction Analysis	Volume Velocity Value Veracity	[FG]
Cadaster/Utilities infrastructure data (BIM)	Planning Infrastructure	Value Veracity	[FG]
Open Data / Public Sector Information (PSI)	Governance Reporting	Value Veracity	[FG]
Archives, historical data (e.g. maps), archaeological data	Planning Culture	Variety Veracity	[FG]
Government agencies	Demographics Integration policies	Value Veracity	[FG]
Time series of EO products (e.g. for climate or weather studies) and EO mission data	Information extraction Analysis	Volume Velocity	Examples in EOSystem: AIRS/Aqua Level 3 Daily standard physical retrieval (2007-2014) TOMS/Nimbus-7 Total Ozone Aerosol Index UV-Reflectivity UV-B Erythemal Irradiances Daily L3 Global 1x1.25 deg V008 (TOMSN7L3) (1978-1993) [FG] Ozone hole was derived from the long term archive data sets by NASA and US observations [I-4]

[109] Anna Donovan, Rachel Finn, Kush Wadhwa, Lorenzo Bigagli, Guillermo Vega Gorgojo, Martin EarthObvsrg Skjæveland, *Open Access to Data*, BYTE Deliverable D2.3, BYTE Consortium, 30 September 2014, p. 55.

[110] Rachel Finn, Anna Donovan, Kush Wadhwa, Lorenzo Bigagli, José María García, *Big data initiatives*, BYTE Deliverable D1.3, BYTE Consortium, 31 October 2014, p. 30.

Linked data: observations and indicators	Information extraction Analysis	Variety Value Veracity	Example: European Environment Agency (http://www.eea.europa.eu/data-and-maps) accessible through SPARQL interface [FG]
Web, social media	Citizen Science Sentiment/trend analysis Early warning Crisis response	Variety Veracity	[FG] EOSystem considering social networking as source of data? Examples: Twitter indications of quake extent [WS] Analysing the web content to determine socio-economic and environmental information and knowledge needs and societal benefits of Earth observations [I-2]
Volunteered EarthObvsgraphic Information (VGI), crowdsourcing	Citizen Science Analysis	Velocity Variety Value Veracity	[FG]
Internet of People (e.g., health monitoring), Internet of Things, Internet of Everything	Automation Information extraction Analysis	Velocity Variety Value Veracity	IoT and IoP — and the "Internet of Location" — are already becoming part of EOSystem [WS] There is a need for more environmental information that depends on the use and integration of Big Data. This will lead to more Big Data solutions. The emergence of IoT will further support this [I-2]

The EarthObvs and a space observation portal have been recognized as primary sources of data, obviously mainly from remote sensing [FG]. The characteristics of the data available through these resources may differ widely: the size may range from the few KB of a vector dataset representing administrative borders, to the GB of a raster coverage resulting from some elaboration, to the PB typical of raw satellite swats by the space observation portal; the timestamp of the data may range from the 70's onward, including the future, for model outputs. Most of the space observation portal's Earth Observation datasets are available online free of charge. Some data products (e.g. Synthetic Aperture Radar data) are even generated on demand, after a specific user requests, also free of charge. The EarthObvs portal provides access to most of the above data sources (Space component, In-situ component,

Open Data/PSI, Government agencies, Time series, VGI, crowdsourcing, IoT), classified. Figure 2 summarizes the data records indexed by the EarthObvs portal catalogue. Future expansions will conceive Linked data and the Service component (models, etc.), for the nine EOSystem SBAs (Agriculture, Biodiversity, Climate, Disasters, Ecosystems, Energy, Health, Water, Weather).

It was noted that all these data sources have a high commercial value [FG]. However, the main data sources are publicly paid and are thus open and free [FG]. This is consistent with the current investments in public-funded initiatives on Open Data / PSI.

	Records	GEOSS Data Core records	Granules	GEOSS Data Core granules	Comments
New Zealand government geodata catalog	2.175	0	2.175	0	Number of records and granules harvested by GEODAB
ISPRA Monitoring network	7.680	0	7.680	0	Number of records and granules harvested by GEODAB
Chile Geoportal	11.647	0	11.647	0	Number of records and granules harvested by GEODAB
South African Environmental Observation Network	14.818	899	14.818	899	Number of records and granules harvested by GEODAB
WIS GISC DWD	143.879	416	143.879	416	Number of records and granules harvested by GEODAB
IGN GeoPortal	50	0	50	0	Number of records and granules harvested by GEODAB
UK Data Gov	6.089	0	6.089	0	Number of records and granules harvested by GEODAB
FedEO	2.551	0	82.355.410	0	The number of granules is obtained by issuing a request with no constraint to each collection, and summing the total number of records
New Zealand Monitoring Network	32	0	32	0	Number of records and granules harvested by GEODAB
NIWA data catalog	188	0	188	0	Number of records and granules harvested by GEODAB
Geoscience Australia	21.301	0	21.301	0	Number of records and granules harvested by GEODAB
Red Vial (Road Network, from Ministry of Public Works) -- from Chile	16	0	16	0	Number of records and granules harvested by GEODAB
HIS Central US	14.331.907	0	14.331.907	0	This number is estimated, in fact the HIS service does not provide this information (number of all available resources). See "Number of Results" section at http://essi-lab.eu/do/view/Gicat/HYDRODetails
NOAA Unified Access Framework Catalog	5.114	0	5.114	0	Number of records and granules harvested by GEODAB
Limites (Administrative Boundaries, from Ministry of Public Works as well) -- from Chile	5	0	5	0	Number of records and granules harvested by GEODAB
SeaDataNet	476	0	1.300.000	0	The estimate of Granules is from http://www.seadatanet.org/content/download/17887/116313/file/ESSI2-5-SDN2-EMODNET-Bathymetry-SchaapApril2013.pdf
EEA SDI Catalog	414	414	414	414	Number of records and granules harvested by GEODAB
GMOS Database	819	0	819	0	Number of records and granules harvested by GEODAB
Global River Discharge Datasets (GRDC/GEOWOW) - Kisters AG	1.928	1.928	1.928	1.928	Number of records and granules harvested by GEODAB
Registered Data	44.417	500	44.417	500	Number of records and granules harvested by GEODAB
IRIS Event	4.163.124	0	4.163.124	0	Number of records and granules harvested by GEODAB
IRIS Station	484.768	0	484.768	0	Number of records and granules harvested by GEODAB
Data Integration and Analysis System (DIAS) - Japan	217	0	217	0	Number of records and granules harvested by GEODAB
NASA Global Change Master Directory	28.108	12.994	28.108	12.994	Number of records and granules harvested by GEODAB
RASAQM	297	297	297	297	Number of records and granules harvested by GEODAB
EGASKRO	408	408	408	408	Number of records and granules harvested by GEODAB
Knossos	536	0	536	0	Number of records and granules harvested by GEODAB
INPE CDSR	863.290	863.290	863.290	863.290	Number of records and granules harvested by GEODAB
ArcGIS Online ESRI	185.000	0	185.000	0	Declared by Provider
BYU World Water Data catalog	15	0	15	0	Number of records and granules harvested by GEODAB
IODE	7.509	135	7.509	135	Number of records and granules harvested by GEODAB
GBIF	19.888.012	0	19.888.012	0	Number of species discoverable. For each species, it is then possible to find related occurrencies.
MEDINA SDI	158	0	158	0	Number of records and granules harvested by GEODAB
Canadian Monitoring Network	828	0	828	0	Number of records and granules harvested by GEODAB
CEOS WGISS Integrated Catalog (CWIC)	1.852	1.821	50.000.000	50.000.000	Declared by Provider
Webservice Energy Catalog	1.165	33	1.165	33	Number of records and granules harvested by GEODAB
PANGAEA	335.877	335.877	335.877	335.877	Number of records and granules harvested by GEODAB
US Data Gov	85.229	467	85.229	467	Number of records and granules harvested by GEODAB
One Geology	438	438	438	438	Number of records and granules harvested by GEODAB
Total	**40.642.337**	**1.219.917**	**174.292.868**	**51.218.096**	

Figure 2 – Datasets available through the EARTHOBVS portal

Our fieldwork confirmed the expectation[111] that benefits could be gained by sharing and integrating the data generated by people, and that also in-situ observatories, including crowdsourcing-oriented platforms and mobile tools, providing a large amount of small heterogeneous datasets, will require Big Data tools in place.

In fact, the interest for "unstructured" data sources, such as the Web, social media, VGI and crowdsourcing listed in the table above, seems to be growing in the environment sector: there are many ways of using social media both directly as sensors, but also as some sort of metadata or data that you combine as relevant to the environment [I-3]. One example is the Citizen Observatory Web (COBWEB)[112] project.

[111] Rajendra Akerkar, Guillermo Vega-Gorgojo, Grunde Løvoll, Stephane Grumbach, Aurelien Faravelon, Rachel Finn, Kush Wadhwa, Anna Donovan, Lorenzo Bigagli, *Understanding and mapping Big Data*, BYTE Deliverable D1.1, BYTE Consortium, 31 March 2015, p. 50.

[112] https://cobwebproject.eu/

The modelling community, as was to be expected, seems less interested in this kind of engagement: Citizen Science is not what we do at DKRZ. Maybe one day DKRZ will be "require[d] to enable access and analysis of the immense amount of social and environmental observation data stream that is collected from intelligent sensors and citizens..." into its numerically generated climate Big Data (i.e. big volume but homogeneous), however, this is not yet discussed (or at most in projects such at RDA or EUDAT, but not seriously envisaged presently) [I-5].

In summary, there is a stress on the heterogeneity of environmental data, gathered from hundreds of countries, several thousand locations, ships, aircraft, land vehicles, satellites [I-6]. Besides, the interlinking of data (e.g. time series, as a special case linking along the time dimension) is seen as a source of new data, providing unexpected insights, especially when typical data sources are couple with non-authoritative, unstructured data, such as social media. It is worth underlying that Europe seems to be leading the Big Data innovation (or revolution) in the EarthObvs spatial sector.

2.2 DATA USES

Value chain analysis can be applied to information systems, such as EOSystem, to understand the value-creation of data technologies. Table 28 contextualizes some of the activities of the BYTE Big Data Value Chain[113] to the environment case study, in relation to the main stakeholders and/or use cases. For example, Environmental Agencies, as intermediate users of environmental data, typically make use of data acquired from sensor networks. EOSystem is mainly related to the final phase of the Value Chain, i.e. the Data Usage phase, as it specifically targets the Society and the decision-makers, which are the end users of the Big Data Value Chain in the environment sector.

Table 28 – Main uses of data in the environment case study

DATA ACQUISITION	
Data streams	National/International Space Agencies (space observation portal and to some extent NASA) [FG] Remote sensing industry [FG]
Sensor networks	Government Agencies (Environmental Agencies) [FG]
DATA ANALYSIS	
Community data analysis	Typical business is to combine data and do some reporting for the municipality [FG] Statistics/reporting [FG]
Cross-sectorial data analysis	Data integration leading to liveable design [FG]
Information extraction Stream mining	Fisheries, mining, oil & gas [FG]
Linked data Semantic analysis	Inventories of data and user needs [FG]
DATA CURATION	
Interoperability	Combining different pieces of data, e.g. near real-time data and historical

[113] Edward Curry, et al. Op. Cit., p. 18.

	data [FG] Federation and sharing of data [FG]
Community / Crowd	Local committees, citizens [FG]
Data quality Trust /Provenance	ICSU CODATA works to improve the quality, reliability, management and accessibility of data of importance to all fields of science and technology [FG]
Incentivisation Human-Data Interaction	E-infrastructure – needed to support open access, legal interoperability, education/changing data culture [WS] The CMIP community propagated open access even for commercial use, with some success; the number of institutes that agree to a free Terms of Use increase [I-5]
DATA USAGE	
Prediction	Crisis, impact forecasting [FG] Insurance [FG] Meteo forecast / nearcast [FG] Final information would be predicted information [I-4]
Decision support	Huge processing demands caused by crisis [FG] Civil protection agencies [FG] Disaster (flooding, thunderstorm, tsunami, earthquakes, wildfires, hurricane, hydrology) [FG]
In-use analytics	In-place processing (Container idea / object-oriented computing / on-line processing of streaming data) [FG] Use of internet locality, temporality, to identify uses [FG]
Domain-specific usage	Farmers, tourism sector, food industry [FG]
Control	Traffic, Anti-terrorism [FG] Policy Enforcement, Global monitoring and control of international agreements (KYOTO, NPT, UN Sustainable Development Goals) [FG] Planning & Control [FG]
Modelling Simulation	Comprehensive virtual representation of the planet (cf. International Society for Digital Earth) [FG] Ozone hole – Climate Change [FG]

The original scope of EOSystem is making Earth observation resources available for better-informed decision-making, particularly in the nine SBAs: Agriculture, Biodiversity, Climate, Disasters, Ecosystems, Energy, Health, Water, and Weather. From this perspective, the uses of EOSystem have focussed on disaster relieve, support to humanitarian actions, and similar initiatives, typically carried on by public bodies. Examples of the myriads of applications that have been realized by means of EOSystem services and data include:

- Forecasting meningitis outbreaks in Africa's "meningitis belt", to help the World Health Organization to target its vaccination programs;
- Providing images free-of-charges to farmers, resource managers and other users so that they can monitor changes in critical environmental variables such as crop growth conditions, crop area and production;
- Integrating ground observations with satellite data to provide accurate maps of the forest canopy and estimates of forest biomass and carbon content.

At present, there is a trend for EarthObvs to evolve into a global venue to support Science-informed decision-making in general, with a growing attention for the industry sector, and for the private sector in general. This may prelude to more commercially-oriented uses of EOSystem data in the future.

Moreover, the IDIB is specifically tasked with capacity building, including human resources, particularly in less-developed countries. This is an important use-case of EOSystem, implemented in programs such as AfriEOSystem[114].

2.3 DATA FLOWS

As a System of Systems, Eosystem is conceived to scale up and accommodate an ever-increasing amount of environmental data and services, offered and consumed by the various EarthObvs participants. Data flows may be virtually unconstrained, originating by one or more data providers, flowing through as many intermediate processes as necessary, before reaching the final user, be it a human or a machine: data is conceived more like streams being continuously generated and collected.

To support this, EOSystem is based on a Service-Oriented Architecture (SOA) and on resource virtualization patterns such as Infrastructure-As-A-Service, Platform-As-A-Service, etc. This is typical of modern Spatial Data Infrastructures (SDIs), like for example the Helix Nebula[115] ecosystem for satellite data, referenced by one of the case study participants: in this ecosystem there are data providers, research institutions providing knowledge (from the analysis of data), EarthObvs app providers, service providers and customers that consume information [FG], backed by a Cloud Computing Infrastructure, which ultimately provides physical and organisational structures and assets needed for the IT-related operation of research institutions, enterprises, governments and society.

In addition, EOSystem provides a central service framework, termed the EOSystem Common Infrastructure (GCI), which is the primary tool where the interaction between data providers and users are materialized. As depicted in Figure 3, the GCI provides a set of capabilities to enable information sharing between multiple data sources and multiple data users. These include a portal, resource registration services, and a number of mediating services, named

[114] http://www.earthobservations.org/afriEarthObvsss.php
[115] http://www.helix-nebula.eu/

brokers, which transparently address any technical mismatches, such as harmonization of data and service models, semantic alignment, service composition, data formatting, etc.

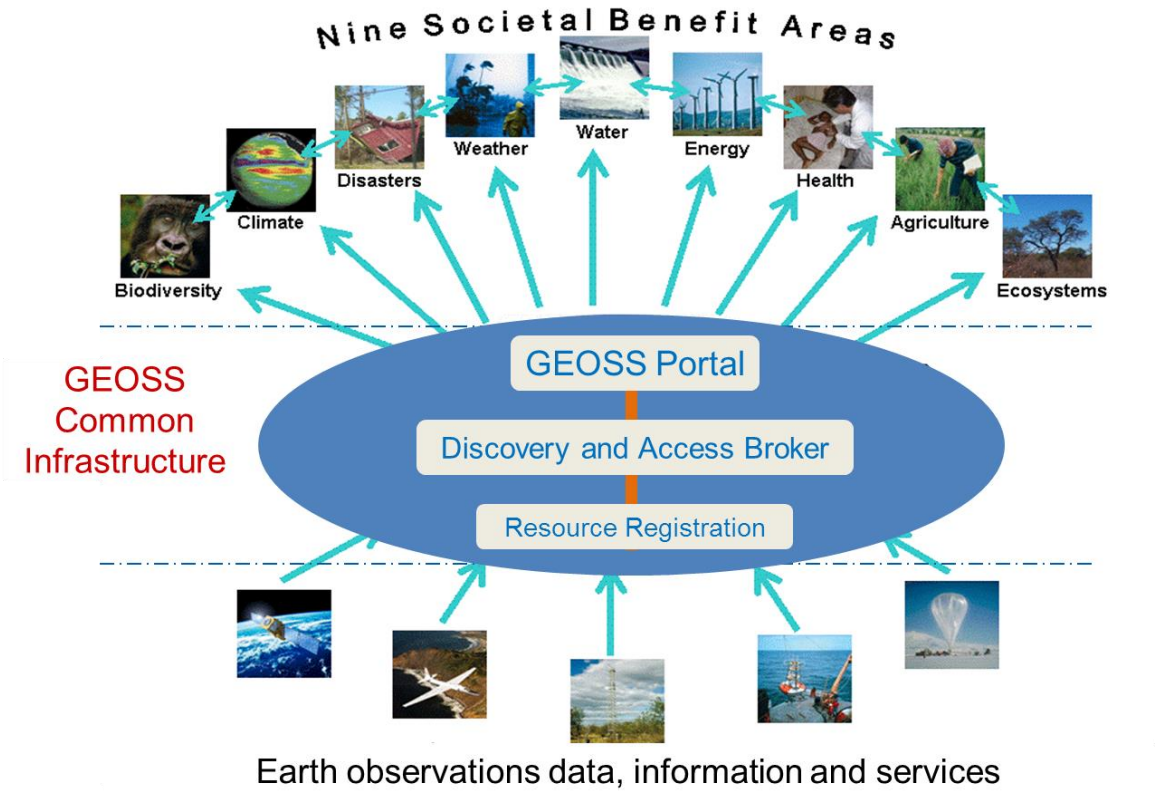


Figure 3 – EOSystem architecture overview

The rationale of this Brokering-SOA is to hide all technical and infrastructural issues, so that the users can better focus on their information of interest (information is the important thing, what would be paid [FG]). For example, the Discovery and Access Broker shown in Figure 3 is in charge of finding and retrieving resources on behalf of the clients, resolving all the interoperability issues and hence greatly reducing the complexity that would be implied by the necessary required interoperability adaptations. Figure 4 represents a data flow through the EOSystem GCI Brokering infrastructure.

As related to the issue of data flow in EOSystem, it is worth mentioning that policies and institutional arrangements are an integral part of the GCI and in general are part of the definition of a SDI, as the fundamental regulatory mechanisms of environmental data exchange. These can range from application-specific Service Level Agreements to overarching frameworks.

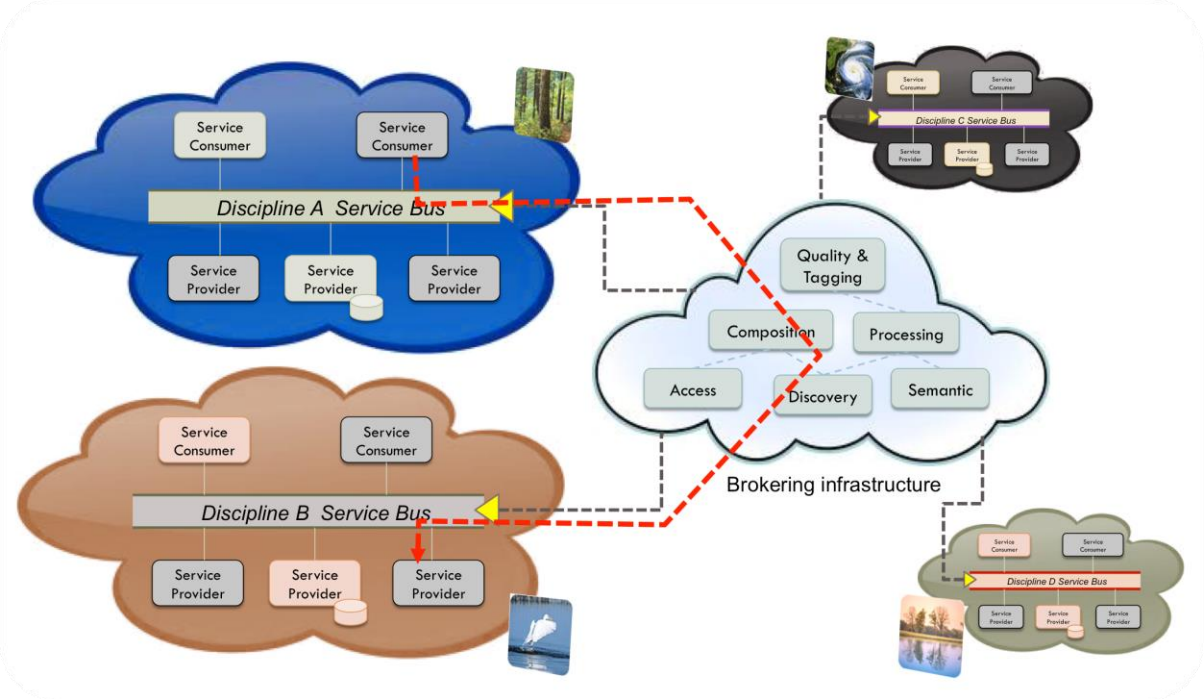


Figure 4 – Representation of a data flow in EARTHOBVSSS

Examples of aspects where environmental policies are advocated or already effective are [FG]:

- Civil protection
- Emergency use or reuse of infrastructure (e.g. UN – SPIDER for disaster response)
- Green energy and infrastructure
- Federated systems
- Fair disclosure of property and environmental findings (e.g. the UK Passport for properties/real estate)
- Multi-lingual support
- Intellectual property (e.g. to avoid overly inclusive patents)
- Public-private partnerships
- Resilience framework (i.e. goals for bringing infrastructure back online)
- Space agency (e.g. Copernicus)
- International Charter for Space and Major Disasters
- EU Common Agriculture policy
- Kyoto protocol (an event in Paris in December will focus on Big Data)
- EEA policy on noise pollution
- Data sharing (e.g. Open Access)

Data sharing policies are obviously most relevant to data flows. Our fieldwork has highlighted the importance attributed to data sharing and the potential impact credited to open access policies in the environment sector (disaster management [is related to] International agreements – in an emergency situation any one government is not equipped to handle disasters that occur across borders; also need for cooperation between local agencies, and data openness is required [FG]; [Space agencies] do not contribute as of yet very much to environmental studies. Some are more defence based. They also keep their own data for themselves. Open access here is key to furthering this [FG]).

EOSystem explicitly acknowledges the importance of data sharing in achieving the EOSystem vision and anticipated societal benefits: "The societal benefits of Earth observations cannot be achieved without data sharing"[116]. The EOSystem Data Sharing Principles recognize the Data Collection of Open Resources for Everyone (Data-CORE) as a key mechanism to advocate openness in data provisioning and address non-technical externalities. The GCI plays a critical role in efficiently and effectively support the implementation of the Data Sharing Principles.

Other policy issues (e.g. security) will probably become more important in the near future (EOSystem needs to facilitate new data integration and to address policies, privacy, etc.: e.g., anonymisation, processes to control use, legal interoperability, quality labelling/trust processes [WS]). Moreover, as we have observed[117], specific sustainability policies will be required, at some point, to secure the long-term sustained operation of the GCI itself. Until now, the GCI has been maintained on a voluntary basis, in accordance with the EOSystem implementation methodology. The Action Plan calls for the EarthObvs Members and Participating Organisations to provide resources for the sustained operation of the GCI and the other initiatives set out. However, the governance of EOSystem beyond the time frame of the Action Plan is not yet defined.

2.4 MAIN TECHNICAL CHALLENGES

From our case study research, the following main technical challenges can be related to the various activities of the Big Data Value Chain[118].

Table 29 – Main technical challenges in the environment case study

Value chain activity	Statement [source]
Data acquisition	Resolution [FG] – also affects data analysis; the choice of an appropriate resolution is application-critical and typically a trade-off with the frequency and range of the acquisition There is a need for more environmental information on local to global scales and on time scales from minutes to years [I-2]
Data analysis	Tricky to find information. Requires getting an overview of the data and getting hold of the data. There is room for improvement here [FG] EOSystem needs to facilitate new data integration [WS] Making a great variety of datasets on different format, temporal and spatial resolution, etc. interoperable [I-3] Translate data into good political and socio-economic decisions [I-1] Not having all algorithms developed to access and analyses the data [I-2]

[116] Group on Earth Observations, "*10-Year Implementation Plan Reference Document*", ESA Publications Division, Noordwijk (The Netherlands), February 2005, p. 139, 205.
[117] Anna Donovan, Rachel Finn, Kush Wadhwa, Lorenzo Bigagli, Guillermo Vega Gorgojo, Martin EarthObvsrg Skjæveland, *Open Access to Data*, BYTE Deliverable D2.3, BYTE Consortium, 30 September 2014, p. 27.
[118] Edward Curry, et al. Op. Cit., p. 18.

	The really important essential variables may not be covered/identified [I-2] Combine real-time and low-latency sensor data with models to generate and distribute environmental information to "customers" [I-2]
Data curation	Quality of data [FG] – arguably the first and foremost aim of data curation: data can be improved under many aspects, such as filling the gaps, filtering out spurious values, improving the completeness and accuracy of ancillary information, etc. In the Eyjafjallajökull crisis, the problem at the beginning was that the volcanic watch data was not accurate (this affects decision-making processes) [FG] Social media and crowd sourced data is generally not trusted. This is especially problematic when combining data sources [FG] Imagine a crisis situation, e.g. a flood in Beijing. The government could not use social media to make a decision [FG] – this is reiterating the issue of trust of non-authoritative sources, such as social media Need to apply methods to transform data into authoritative source, e.g., W3C [WS]
Data storage	Sustainability is an important requirement. There is a continuous access of data – its availability has to be guaranteed [FG] An important issue is the long-term maintenance of the infrastructure [I-1] It would help to increase both storage and transfer velocity [I-5] Data parallelism [FG]
Data usage	Data access is a challenge [FG] Interpretation. There is an institutional gap between mapping authority and the scientists [FG] Lack of standards, industrial competitors that use standard violations to strengthen their position [I-2]

Our fieldwork confirms the significant technical challenges raised by data-intensive applications in the environment sector[119]. They encompass a wide range of applications: from disciplinary sciences (e.g. climate, Ocean, EarthObvslogy) to the multidisciplinary study of the Earth as a System (the so-called Earth System Science). They are based on Earth Observation, requiring handling observations and measurements coming from in-situ and remote-sensing data with ever growing spatial, temporal, and radiometric resolution. They

[119] Rajendra Akerkar, Guillermo Vega-Gorgojo, Grunde Løvoll, Stephane Grumbach, Aurelien Faravelon, Rachel Finn, Kush Wadhwa, Anna Donovan, Lorenzo Bigagli, *Understanding and mapping Big Data*, BYTE Deliverable D1.1, BYTE Consortium, 31 March 2015, pp. 51-52.

make use of complex scientific modelling for deriving information from the large amount of observations and measurements.

The opinions gathered reiterate that data access, the basic requirement of any use case, is a hindering factor (it is hard for new players to access the data [FG]). This issue is also reinforced by the lack of standardization, particularly of the data format (XML standardized access needs to be improved [FG]). From this perspective, the implementation of open access policies is considered a facilitating factor (we are going to promote, freely open available as much as possible. So it means everyone can access to the data [I-4]). Open access policies are considered effective also to mitigate other technical issues (open access […] may help because people spent so much time to install the necessary authorization and authentication software [I-5]; optimization of utilities through data analytics: there is some risk that it may be hampered by not distributing the data under open access conditions [I-5]).

However, there is a general perception that technical challenges are easy to overcome [FG], and that the real issues are policy-related, e.g. data quality (do you benefit from open data? Yes – orders of magnitude decrease in cost of collection. Are there disadvantages? Yes – maintenance of quality control [I-6]).

Speaking of the scientists' efforts to work around organizational barriers, some have spoken of an "organizations vs. science" [FG] conflict, which would require an overall cultural change (E-infrastructure needed to support open access, legal interoperability, education/changing data culture [WS]).

2.5 BIG DATA ASSESSMENT

In our fieldwork we have collected a number of testimonials, impressions and opinions about the adoption and challenges of Big Data in the environment sector. With this input we have elaborated Table 19, containing the main insights and the statements that support them.

Table 30 – Assessment of Big Data in the environment case study

Insight	Statement [source]
Environment sector: Big Data has always been there	Not clear what is so new about Big Data that changes what EOSystem is doing… has already been doing Big Data for more than a decade [WS] EOSystem is facilitating access to lots of data [WS] Big data is nothing new: there is more data now, but technology is also improving [FG] EOSystem has always been about Big Data in environment sector! [WS] EarthObvs has being a Big Data organisation or a Big Data handler since the very beginning [I-3] This is obvious... [I-5] We already have Big Data. And it is going to get much bigger [I-6]

	There is so much data and the philosophy of getting the data from one place to another, has driven us to the solution that instead of bringing the data to the processing you bring the processing out in the cloud to the data. So that's a new way of a different way of thinking and very different way of doing things [I-3]
Variety is a very big challenge, and growing	Greater variety of data, e.g. crowdsourcing, etc. has implications for EOSystem [WS] Variety is an important factor in environment data – needs an interdisciplinary mind-set to fully analyse and understand the data [FG] [Through EOSystem] you can put together and get more information and different information, more efficiently than you did before [I-3] So the value would be integration of the variety of the datasets into final product as predicted information [I-4]
There are no shared Veracity, Value, and Validity criteria	Validation and verification of data is up to members, not EarthObvs [WS] EarthObvsGLAM (Global Agriculture Monitoring) information for decision making; member states take responsibility for the information development and validation [WS] EarthObvs and EOSystem could serve as forum for airing issues and problems (complementary to other efforts?) [WS] EarthObvs has to be supportive and follow member policies [WS] DKRZ is also involved in Veracity (quality assurance), but also in a way which is not so interesting: the data need no protection, as they are no individual-related details, and nobody objects to in-depth analysis - maybe for a while because of authoring aspects, but besides everybody agrees to open data for access [I-5]
Policy issues seem bigger than technical/infrastructural ones	The biggest challenges lies in the complexities related to humans and organizational issues. In particular it is a challenge that the technology develops faster than the organisational and human issues are being addressed and solved [I-3] Difficulties: mostly institutional; shared vision; capacities at human-infrastructure-institutional levels [I-1] Internal national policy is one of the barriers [I-4] Enable under-funded public sector to manage public resources responsibly, without private corporation creaming excessive profits or restrictively owning the means of production [I-6]

The question whether Big Data is a radical shift or an incremental change for the existing digital infrastructures for environmental and EarthObvsspatial data[120], seems to lean on the second option (We are slowly discovering the potential and benefits of Big Data [I-1]). In fact, Environmental Sciences have been in the forefront in many initiatives trying to realize the e-Science vision (a "global collaboration in key areas of science, and the next generation of infrastructure that will enable it"[121]) and its data-oriented underpinning. Many scientists and technologists are advocating an entirely new approach to science based on data intensive scientific discovery, named the Fourth Paradigm[122] and supported by Big Data.

While Big Volume, big Variety, and high Velocity are typical issues of Environmental Sciences data systems, Variety is reported as a very important challenge, and most likely to become even more in the future, with the uptake of crowdsourcing, Internet of Things, etc. An aspect of Variety that is worth underlining regards the heterogeneity of data resolution: the coverage of the Earth is typically not uniform at every resolution, but instead presents gaps that require complex interpolations to integrate the existing data at different resolution levels. One of the strategic goals of EOSystem is a comprehensive coverage of the planet. Noticeably, the modelling community seems to remark its specificities with regards [...](climate model data includes just 2 Vs: volume and velocity [I-5]).

As commonly recognized in the scientific debate, quality of data is the biggest challenge. While most would agree on how to quantify and address Volume issues, there is no shared view on "quality criteria", such as Value, Validity and Veracity. Addressing these aspects seems to have been postponed until now, and delegated to other parties. Workshop participants seemed particularly weary of taking strong positions on this, although admitting criticism on the quality of the data available on EOSystem.

As we noted in the previous section, there is a general perception that technical challenges are easier to overcome than policy issues, especially those arising at the intersection between the public and the private sector. There are concerns that private actors abuse public resources (in terms of data made openly available), without returning on the investment.

3 ANALYSIS OF SOCIETAL EXTERNALITIES

According to the case study methodology[123], we have investigated the external (i.e. impacting or caused by third parties) barriers and enablers to the identified data-intensive environmental processes. In fact, there exists an obvious relationship between the externalities of an activity and the consequent reactions from affected third parties. If an activity causes a negative externality, then the affected party would oppose it, and hence appear as an (external) barrier. Likewise, parties taking advantage of an environmental process would facilitate it, resulting as enablers. We have restricted our interest to cases where the affected third parties have

[120] Anna Donovan, Rachel Finn, Kush Wadhwa, Lorenzo Bigagli, Guillermo Vega Gorgojo, Martin EarthObvsrg Skjæveland, *Open Access to Data*, BYTE Deliverable D2.3, BYTE Consortium, 30 September 2014.

[121] Hey, Tony, and Anne E. Trefethen. 2002. "The UK e-Science Core Programme and the Grid." International Journal for e-Learning Security (IJeLS) 1 (1/2): 1017–1031.

[122] Hey, T., Tansley, S., Tolle, K. (Eds.), 2009. The Fourth Paradigm: Data-intensive Scientific Discovery, p. 252. Microsoft Corporation edition.

[123] Guillermo Vega-Gorgojo, Grunde Løvoll, Thomas Mestl, Anna Donovan, and Rachel Finn, *Case study methodology*, BYTE Deliverable D3.1, BYTE Consortium, 30 September 2014.

some relevance for the Society at large, as per the scope of BYTE. Figure 5 depicts the intuitive conceptual model we have adopted to refine our analysis.

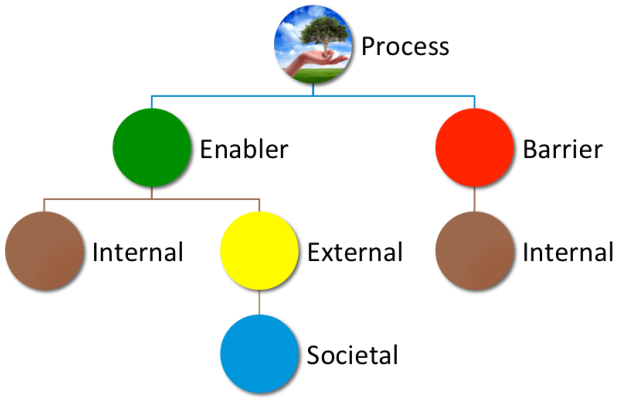


Figure 5 – model of externalities in the environment use-case

The outcomes of the analysis are somewhat blurred, as most external factors typically have both positive and negative aspects and can be seen as double-edged swords (the benefits also come with risks [WS]; benefits of using data to support SBAs inevitably comes with risks of potential misuse of data [WS]).

We have also grouped the identified externalities in four classes: economical, social & ethical, legal, and political. This classification is also somewhat arbitrary. The participants in our fieldwork often found it difficult to clearly assign an impact to a dimension and felt that there were clear connections and flow between them [FG].

3.1 ECONOMICAL EXTERNALITIES

We include in Table 31 the economical externalities that we have found in the environment case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 31 – Economical externalities in the environment case study

Code	Quote/Statement [source]	Finding
E-PO-BM-2	There are new, different business models [FG] EarthObvsdata as a tool for creating a new marketplace – this is the cloud part of the ecosystem. EarthObvsdata could be something similar to GPS for the European economy [FG] There are many European agencies (based on European projects) that are inter-governmental. Some examples: EPOS, USGS, IRIS, ESA, CEOS, CERN. Since these agencies are leading the industry worldwide, there is potential for a marketplace [FG]	Innovative business models (closer linkages between research and innovation)
E-PO-BM-1	Everything should be free and open. There is business value in this, enabling people to be creative and to create value. In addition, governments get value by these new businesses [FG]	Opportunities for economic growth (new products and

	New services yes; see e.g. Climate Service Center 2.0 (former CSC)[124] [I-5] From the Big Data perspective, certainly we have a market in the public sector right now [I-4] Green businesses [FG] – synonym for sustainable business: an enterprise that has minimal negative impact on the global or local environment, community, society, or economy; typically characterized by progressive environmental policies The open data policy will also provide many new opportunities for private-public partnerships and help to develop economic activities [I-2] Opportunity for new jobs and new businesses on the basis of Big Data [FG]	services based on open access to Big Data)
E-PC-TEC-1	What about value added processed data based on social media? [WS]	Gather public insight by identifying social trends and statistics, e.g. epidemics or employment rates (see social computing)
E-OO-BM-1	Environmental agency in Japan do not use satellite data, they use their own monitoring data. However there are changes in funding that demonstrate that a change may be taking place and links between the environment sector and space agencies are being forged. More engagement with the space agencies could be considered to be a benefit of Big Data [I-4] Opportunities for knowledge economy [FG]	Opportunities for economic growth through community building (sharing information and insights across sectors)
E-PC-BM-2	Better utilisation of current services, extended operational life (extended satellite life time) [FG]	Better services, e.g. health care and education, through data sharing and analysis (need to explain the benefits to the public)
E-OC-DAT-1	Standardisation [FG] – data-intensive applications typically have repercussions on technological development and create momentum for standardization activities	Enhancements in data-driven R&D
E-OO-DAT-1	Inequality in data access [FG] Fear of existing business, small businesses may suffer [FG] Big data may favour big players. There are not equal	Inequalities to data access (digital divide between Big Data players and the rest)

[124] http://www.climate-service-center.de/

	opportunities for small and big players [FG] The Big Data and the technical issues related to that will work against many actors. Those actors able to deal with Big Data can also decide if they want to develop services and hence they will be competitors to those who will use the data [I-3] Rising inequality caused by elite skills in data [FG] Unequal opportunities for SMEs. Unequal access for users to services and data – who owns the most money has the best access to data [FG]	
E-PO-DAT-1	I think it might be good for them [private sector] to use public free-of-charge datasets [I-4] There are public repositories. Storage costs are huge, although governments and the commission will pay [FG] We are starting to make collaboration with the private sector. Because private datasets might be more accurate than public datasets [I-4] Big global private sector 'cloud' owners such as Google, Amazon, etc. [might endanger the development towards the use of Big Data] [I-6] I don't like to use the term competitor, but certainly the private sector, Google, ESRI, Microsoft, they are kind of that [I-4] We would certainly have questions, on what relationship EarthObvs will have to the private sector, such as Google, ESRI, and Microsoft [I-4]	Open data puts the private sector at a competitive advantage (they don't have to open their data and have access to public data)
E-OC-BM-7	Matthew Effect. First mover advantage drives out competition [FG] IT silos appearing, whether proprietary or regional and national solutions [I-6]	Reduced market competition (creation of a few dominant market players)
E-OO-BM-7	Current supercomputers, that generate the Big Data, need several MW of electricity to run [I-6] Cost of renewable energy [I-6] Cell phone data – impact of power outages? [WS] Inefficiencies caused by excess of pre-computed data [FG] The mounting environmental crisis may require that more resource are used to address the crisis instead of generating environmental information that could help to limit the crisis or avoid it [I-2]	Resource allocation and inefficiencies associated to big data

On the positive side, the use of big data in the environment is credited with having strong implications on the economic growth (providing reliable environmental data has a strong impact on economies (e.g. sea data for fishing nations and weather data for tourism) [FG]),

for the mere direct effects on the IT sector (opportunities for infrastructure/hardware/data centres [FG]; rent-sharing possibilities for computing [FG]).

The implication seems especially interesting, given that, as we noted in section 2.1, Europe has a prominent role in innovation in the EarthObvsspatial sector (Europe is leading the EarthObvs industry [FG]). According to one of the participants of the focus group, this could pave the ground for a new vision in European cooperation (we can create a new model to change things based on collaboration in Europe. It should be purely democratic, with our rules [FG]).

However, the Big Data revolution could as well be seen as a threat by traditional services, for example in the weather forecasting sector (so many service institutions now around climate services. Model data are mostly free for commercial use as I said before. Weather prediction centres are more reluctant [I-5]).

Another negative implication mentioned is the possibility of increasing market inequalities and consolidating the dominant position of the big players. This concurs with the allegation of an underground "private vs. public" conflict, mainly consequence of the promotion of open access policies by public bodies, which may put the private sector (and again, especially the big players) to a competitive advantage.

However, opinions were also expressed that counterbalance this worry, recognizing that niche positions may still provide significant economical opportunities for new/small companies. Examples quotes are:

> [current main actors in the Big Data arena (e.g. Google, ESRI, USGS, ESA)] have the advantage of being able to manage huge computing infrastructures and therefore can provided important processing capabilities. However, as big companies/agencies, they are not dedicated to one specific community of users and therefore provide some generic solutions and not tailored applications/solutions [I-1].
>
> Google doesn't have the competence to do the analysis [FG].
>
> [There are] opportunities for big players and small ones [FG].
>
> Smaller companies can thrive in resilient networks [FG].

3.2 SOCIAL & ETHICAL EXTERNALITIES

We include in Table 32 the social and ethical externalities that we have found in the environment case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 32 – Social and ethical externalities in the environment case study

Code	Quote/Statement [source]	Finding
E-PC-ETH-1	Democratization of knowledge [FG] Vast opportunities for crowd-sourcing and to involve the public [FG] Give people the tools they need, to help themselves	Increased citizen participation

	[FG] Measures or tests of preparedness for communities [FG] Outcome measures for community resilience [FG] More realistic models of human behaviour under crisis [FG]	
E-OC-ETH-1	Pervasive technology (human sensor), health will improve, better handling of environmental causes of ill health [FG] Liveability of urban systems enhanced [FG] Quality of life (monitoring of air quality) [FG] Enhanced quality of living caused by improved job opportunities [FG] Affordable climate resilience studies caused by enhanced scalability [FG] Lower price for resilience [FG]	Safe and environment-friendly operations
E-PC-BM-1	One of the positive externalities is improved decision making for sustainability. We are now in the process of making EOSystem better aligned to the needs of the big Post-2015 agendas in sustainable development and disaster risk management, which will lead to many positive externalities, including (hopefully) progress towards more sustainability, more environmental safety, reduced disaster risk [I-2]	Tracking environmental challenges
E-OC-ETH-2	Better self-assessment profiles and templates enhancing community awareness [FG] Ability for individuals to be better aware of risks [FG] Higher reliance [FG]	Increase awareness about privacy violations and ethical issues of Big Data
E-CC-ETH-1	Concerns over privacy (always being tracked) [FG] Use of Big Data in urban settings; e.g., implications of using cell phone data for crowd control [WS]	Continuous and invisible surveillance
E-OO-ETH-1 E-OC-ETH-7	Possible manipulation of visual representations of data [FG] Need to formulate 3D and 4D ethics[125] [FG]	Market manipulation Consumer manipulation
E-PC-ETH-5 E-OC-ETH-11	Danger of predefined, pre-chewed questions [FG] Less quality of data from crowdsourcing [FG]	Public reluctance to provide information (especially personal data)
E-OC-ETH-4	Leaving people behind, consequences of a digital divide [FG] Potential pogroms caused by misuse of data [FG]	Discriminatory practices and targeted advertising (as a result of

[125] See also: http://3dok.info/WordPress3/gwf-2014-award-to-the-3d-ethics-charter-committee/?lang=en

	Blame seeking behaviours, and “witch hunts” inhibiting experiments [FG]	profiling and tracking private data)
E-OC-ETH-12	If you look at the social media, where it’s none authoritative data, you have the possibility of creating false data and mess up the total image, understanding of the situation. So you have fraud and you have actors who deliberately want to misinform, just for sabotaging even relating to the environment you have political or economic interest and just people for fun [I-3]	"Sabotaged" data practices

On the positive side, a rather important social externality is the effectiveness of data-intensive approaches in improving the governance of environmental challenges, supporting safe and environment-friendly operations. This has implications on the robustness of the environment to recover after stressing events (resilience), especially in urban context, as well as on the actual quality of life and human health. A growing reliance on environmental data also increases social awareness and participation, both by individuals and communities.

On the other side, big-brother-effect and manipulation, real or perceived, can be problematic. In fact, as human society is an integral part of the environment, especially in urban context, the fear of data abuse, privacy violation and the like, may hamper participation and engagement and, for example, jeopardize crowdsourcing just where it could be the most effective strategy.

More subtly, also excessive trust in data-intensive applications has been highlighted as a possible negative implication, in that it would encourage the false believe that the dynamics of the environment can be captured quantitatively, overlooking qualitative aspects that, instead, remain fundamental to comprehend it, for the time being (Overconfidence in technology [FG]; Quantified Earth (as in quantified self) may lead to a mind set whereby we trust too much in data [FG]).

Whatever the quantity of data and metadata, and the complexity of theories and models, it seems that a holistic approach is still necessary in the environment sector, to interpret them (thinking too much about the data and the metadata, but not the question or knowledge which is being sought [FG]).

3.3 LEGAL EXTERNALITIES

We include in Table 33 the legal externalities that we have found in the environment case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 33 – Legal externalities in the environment case study

Code	Quote/Statement [source]	Finding
E-PO-LEG-2	Current privacy laws are hindering innovation [FG] IPR concerns could slow down the process (no credit to data provider), negative impacts on privacy (always tracked), Data liability (data quality) [FG] Some stakeholders don’t want to know because of potential liabilities [FG]	Reduced innovation due to restrictive legislation

	There are also liabilities issues, especially for authorities. They may take wrong decisions because of incorrect information [FG] Current laws are curtailing public use [FG] Rules to regulate crowd sourcing, privacy issues [might endanger the development] [I-2] Open knowledge initiatives are hindered by intellectual property rights [FG] Better informed and precise legislation for environmental protection, preservation (evidence-based legislation) [FG] Potential new [legal] frameworks for novel market and business models [FG]	
E-PC-LEG-4	Inequitable loss of privacy [FG] – as data distribution is not symmetric, some parties may be more exposed to privacy abuse than others, e.g. e.g. individual citizens with respect to corporations which hold information about them	Threats to data protection and personal privacy
E-PP-LEG-2	IPRs are a mess! This is a hindrance [FG] How do you maintain legal compliance? With difficulty. We employ a full time legal professional to give internal and external advice [I-6]	Need to reconcile different laws and agreements, e.g. "right to be forgotten"
E-OC-LEG-4 E-PC-LEG-5	Legal reform is needed to preserve the commons of the data IPR control is needed. Content creators are giving up data authorship to Google and Facebook. A fair market needs control in the middle [FG] Members don't currently "own" social media data [WS]	Threats to intellectual property rights Threats to intellectual property rights (including scholars' rights and contributions)
E-PO-LEG-1	Lack of definition about who can use the data [FG] Lack of definition under which circumstances the data can be used [FG]	Lack of norms for data storage and processing/use

The growing reliance on data in the environment sector is certainly highlighting many shortcomings of the current legal frameworks, e.g. on IPR, privacy, authorization to use the data. Potential problems are obviously more prominent when considering different legislations. For example, the principle of full and open exchange of data, as promoted by the EarthObvs Data Sharing Principles, is simply inconsistent with some of the current national policies.[126]

[126] Anna Donovan, Rachel Finn, Kush Wadhwa, Lorenzo Bigagli, Guillermo Vega Gorgojo, Martin EarthObvsrg Skjæveland, *Open Access to Data*, BYTE Deliverable D2.3, BYTE Consortium, 30 September 2014.

Legal support for citizens in data-related issues is arguably going to become a public service, in the future. Besides, incompatibilities in the legal frameworks in different countries are seen as inhibitors that need to be adapted, in order to remove legal barriers.

Hence, as a possible positive outcome, the current trend for data-intensive applications in the environment sector, prompting for better informed and more precise legislation, may lead to new cross-boundaries legal frameworks, based on sound evidence.

3.4 POLITICAL EXTERNALITIES

We include in Table 34 the political externalities that we have found in the environment case study. For each row we indicate the externality code from Table 55, the specific finding and a set of statements from the case study data sources that support it.

Table 34 – Political externalities in the environment case study

Code	Quote/Statement [source]	Finding
E-PC-LEG-1	One may say that the openness of climate change data gives the citizens the change to control whether politics react adequately with respect to the threat [I-5] Enhanced accountability [FG] – the managers of public good can be held more accountable of their decisions, when they have to base them on observations and measurements	Transparency and accountability of the public sector
E-CC-TEC-1	Enable many more countries and organisations to develop sophisticated use of weather and climate data with increased reach [I-6] Democratization of knowledge about politics… [FG] A strong participation of the public sector can help to make environmental data, information and knowledge and the services that give access into a public goods available to all [I-2] Benefit for planning, both rural development and urban [FG] Effective design of infrastructure [FG] Improved property values [FG] Improved “surveillance” (government decisions on civil infrastructure) [FG] Evidence-based policy making, informed by Big Data [FG]	Support communities and governance
E-OO-DAT-2	Over-dependency on centralized computer services Unintended effect will be like the emergence of Google Maps who became a kind of standard application and this has forced the entire community to develop applications as simple as Google Maps. This can also capture a lot of users and what happens if the system fails or is no more maintained? [I-1] The guy who has control of the data has control of the whole	Dependency on external data sources, platforms and services (due to dominant position of big players)

	value chain. The dangerous part is in the middle, the IT infrastructure [FG]	
E-OC-BM-8	Privatising the Commons [FG] – the increased use of data may stimulate the private interest for assets that belong or affect the whole of a community, such as communication infrastructures, public knowledge bases, etc.	Privatization of essential utilities (e.g. Internet access)
E-PP-LEG-1	Gravity information is not generally sensitive, but it is not possible in Tibet (due to China). There are political issues in China, Cyprus and Russia with EarthObvs data [FG] EarthObvs political frictions - using environmental data to justify sanctions against specific countries (exclusion), using Big Data to meet specific political ends (e.g. pinpointing natural resources of poorer countries for exploitation by richer countries) [FG]	EarthObvspolitical tensions due to surveillance out of the boundaries of states

As a positive externality of Big Data in the environment sector, political decisions are expected to be more transparent and accountable, since choices will have to based on measurable and observable indicators. Policy making informed by scientific, data-grounded evidence is also the main objective of EOSystem, summarized by the motto "for sound science to shape sound policy".

Negative externalities from the political viewpoint include the risk of depending on external sources, particularly big players. Google was indicated as a specific element of concern, in our fieldwork, for its demonstrated capacity to impose its commercial products as de facto standards, causing an implicit vendor lock-in for their maintenance and evolution.

In addition to the technical problems mentioned in the previous sections, open access policies are seen as possible means to mitigate these issues too (solution to political negative externalities is to advocate for open access policies to ensure a more equal access. Or enforce a minimum level access if not open [FG]).

The use of EarthObvsgraphical data was also indicated as a potential source of EarthObvspolitical tensions, e.g. with regards to disputed or otherwise sensitive areas. Again, this implication seems especially interesting, given that, as noted in section 2.1, Europe leads the innovation in the EarthObvsspatial sector (Europe is leading the EarthObvs industry [FG]). Hence, if appropriately leveraged, the shift to a more intensive use of data in the environment sector may put Europe in a primary role on the EarthObvspolitical scene.

4 CONCLUSION

Big Data seems more of an incremental change than a major shift, in the environment sector. In fact, the typical Big Data issues of Volume, Variety, and Velocity are considered inherent to the environment sector. In particular, Variety seems to be a yet rising challenge, mainly because of the current trends of direct citizen engagement, such as Citizen Science, crowdsourcing, and VGI.

Solutions for the "quality" issues captured by the remaining V's of Veracity, Value and Validity have not gained much consensus, until now. The environment sector continues to be highly fragmented from that regards, and even global endeavours such as EarthObvs keep a cautious attitude towards quality.

In general, however, the sensation is that technicalities are not the main difficulties, but rather issues of IPR, privacy, use, and other governance aspects that will require an overall shift of mind set. Often surfacing in the debate on Big Data in the environment sector is the perception that private and public interests are clashing, and that the enormous investment already allocated (and the amount needed for the future) burdens on the community, while being mostly reaped by the private sector.

As reported by the EOSystem Data Sharing Action Plan[127], various data providers fear that full and open exchange of data, metadata and products could be a threat to commercially viable information. Further, many providers cannot see a clear articulation of a business model linked to the adoption of the principle of full and open exchange. For these reasons, many private operators are reluctant to provide open access to their data. This amplifies the competitive advantage of the private over the public sector.

There are myriads of applications in the environmental sector. The scope of EOSystem spans as many as nine area of societal benefits (Agriculture, Biodiversity, Climate, Disasters, Ecosystems, Energy, Health, Water, and Weather), helping developed and developing nations battling drought and disease, emergency managers making evacuation decisions, farmers making planting choices, companies evaluating energy costs, and coastal communities addressing concerns about sea-level rise.

Our fieldwork has highlighted many interrelated implications of data-intensive applications in the environment sector, particularly as regards their impact on Society. Our analysis is somewhat blurred and shows that most externalities have both positive and negative impacts on Society. Our classification in economical, social & ethical, legal, and political externalities is also somewhat arbitrary, as they often impact on multiple dimensions.

A conclusion we can reach is that Europe is leading innovation in the EarthObvsspatial sector and should carefully leverage this leading position to play a primary role in the on-going shift to a more intensive use of data in the environment sector.

[127] Group on Earth Observations, *EARTHOBVSSS Data Sharing Action Plan*, EARTHOBVS-VII Plenary document, Beijing, China, 3-4 November 2010. https://www.earthobservations.org/documents/EarthObvs_vii/07_EARTHOBVSSS%20Data%20Sharing%20Action%20Plan%20Rev2.pdf

HEALTHCARE CASE STUDY REPORT

SUMMARY OF THE CASE STUDY

Big data utilisation is maturing in the public healthcare sector and reliance upon data for improved efficiency and accuracy in the provision of preventive, curative and rehabilitative medical services is increasing rapidly. There exists a myriad of 'types' of health data, although the BYTE case study focuses on the use of genetic data as it is utilised by a public health data driven research organisation, pseudonymised as the Genetic Research Initiative (GRI), which is conducted within a health institute at a medical university in the UK. In the healthcare sector, raw genetic data accounts for approximately 5% of the big data utilised.[128] GRI facilitates the discovery of new genes, the identification of disease and innovation in health care utilising genetic data. In doing so, GRI offers BYTE a unique case study of societal externalities arising in relation to big data use, including economic, social and ethical, legal and political externalities.

As this case study focuses on a health initiative that utilises big data for gene identification, it involves stakeholders that are specific to the initiative, including data providers (patients, clinicians), data users (health care professionals, including geneticists), enablers (data engineers, data scientists and computational geneticists). Additional desktop research and discussions at the BYTE Focus Group identified a number of additional stakeholders involved with big data and healthcare more generally, both in the public and private sector, including, for example, secondary stakeholders (pharmaceutical companies, policy makers). Whilst this report does not present an exhaustive list of current and potential stakeholders involved with big data in healthcare per se, the stakeholders identified in this report mirror stakeholders involved in similar data initiatives within the sector and suggest prospective stakeholders that are not yet fully integrated in big health data.

The data samples used, analysed and stored by GRI do not, in isolation, automatically constitute big data, although there exists a number of opportunities to aggregate the data with other similar health datasets, and/or all the genetic data samples at GRI, to form larger datasets. However, the data samples are often combined for the purpose of data sequencing and data analytics and require big data technologies and practices to aid these processes. The aggregation of health data extends the potential reach of the externalities produced by the utilisation of health data in such initiatives. For example, GRI's research can lead to improved diagnostic testing and treatment of rare genetic disorders and assist in administering genetic counselling. GRI's utilisation of genetic data also highlights when more controversial impacts can arise, such as in the case of ethical considerations relating to privacy and consent, and legal issues of data protection and data security for sensitive personal data.

1 OVERVIEW

The Genetic Research Initiative (GRI) provides BYTE with an opportunity to examine the utilisation of health data that raises a number of issues and produces a number of societal impacts. GRI provides an important service to members of the community affected by rare genetic disorders, as well as contributing to scientific and medical research. GRI comprises a management team and an access committee, both of which are made up of clinicians and

[128] "Big Data in Healthcare", *BYTE Focus Group*, London, 10 March 2015.

scientists. As a research initiative, GRI prioritises data driven research to produce data driven results. GRI also provides BYTE with evidence of positive impacts of this research, as well as evidence of the barriers associated with big data use in this context.

Data usage adoption is maturing in the public healthcare sector and reliance upon big data for improved efficiency and accuracy in the provision of preventive, curative and rehabilitative medical services is increasing rapidly. However, the expense associated with public healthcare is also increasing within a largely publicly funded sector that is constantly trying to manage the growth of expenditure. Despite this tension, healthcare organisations are making progress with the collection of data, the utilisation of data technologies and big health data specific information practices to efficiently capture the benefits of data driven healthcare, which are reflected in the externalities produced by this usage. For example, an economic externality is the reduction of costs associated with healthcare. Other benefits specific to genetic data use in the case study include more timely and accurate diagnoses, treatment and care insights and possibilities. Nevertheless, given the sensitivity of the personal data handled for healthcare purposes, the ethics of privacy and legal data protection risks arise. Another major barrier identified in the public sector is funding restrictions, which dictates the rate at which technologies and infrastructure can be acquired, and further research in data analytics can be undertaken to exploit the riches of (big) datasets. These trends are reflected in genetic data utilisation by GRI, the focus of the BYTE case study on big data in healthcare.

1.1 STAKEHOLDERS, FOCUS GROUP PARTICIPANTS AND OTHER INFORMATION SOURCES

Stakeholders, interviewees (I) from GRI, the case study organisation, and focus group participants (FG) are the main information sources for this report. Additional desktop research has been undertaken into big data and health data for the BYTE project generally[129], in the writing of a definition of big health data for Work Package 1 of BYTE, and as well as in preparation for this case study. The BYTE case study on big data in healthcare examines genetic data collection and use, and as such, involves stakeholders specific to that initiative. Other relevant stakeholders are identified in the BYTE Stakeholder Taxonomy, and together, they assist us in identifying current and potential roles played by stakeholders on the healthcare sector more generally. Case study specific stakeholders are identified in Table 35.

Table 35 Organizations involved in the healthcare case study

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
Public sector health research initiative	Healthcare, medical research	Early majority/ Late majority	Analysis, storage, usage	Support role Factory role
Geneticists	Healthcare, medical research,	Late majority/ laggards	Analysis, curation, storage	Factory role
Clinicians	Healthcare (private and public)	Late majority/ Laggards	Usage	Support role
Data scientists	Healthcare, medical	Early majority	Curation, storage, usage, analysis	Factory role

[129] See BYTE Deliverable 1.3, "Big Health Data", *Sectorial Big Data Definitions, 31* March 2015.

	research			
Pharmaceutical companies	Commercial	Early adopters	Acquisition, usage	Turnaround role
Translational medicine specialists	Healthcare (private and public sector)	Mixed	Acquisition, usage	Turnaround role
Public health research initiative	Healthcare, translational medicine specialist	Early adopters	Analysis, usage	Turnaround role
NHS Regional genetics laboratory	Public sector healthcare laboratory	Mixed	Acquisition, storage, usage, analysis	Factory role
Charity organisations	Civil society organisations	Laggards/ NA	Usage	Support role
Privacy and Data protection policy makers and lawyers	Public and private sector	N/A	N/A	Strategic role
Citizens	Society at large	N/A	N/A	N/A
Patients and immediate family members	Public sector	N/A	N/A	Support role/ turnaround role

Interviewees and focus group attendees are the major source of information for the BYTE case study on big data in health care and are detailed in Table 36.

Table 36 Interviewees of the culture case study

Interviewee/ FG participant	Organization	Designation	Knowledge	Position	Interest	Date
I1	Public health initiative	Manager, Geneticist	Very high	Supporter	Very high	10 December 2014
I2	Public health initiative	Manager, Clinical geneticist	Very high	Supporter	Very high	8 January 2015
I3	Public health initiative	Computational Geneticist/ Bio-mathematician	Very High	Supporter	Very high	14 January 2015
I4	Public health initiative	Translational medicine specialist	Very high	Supporter	Very high	18 March 2015
FG5	Research and consulting (pharmaceutical)	Area Director	Very high	Supporter	Very high	9 March 2015
FG6	Bioinformatics Institute	Researcher	Very high	Supporter	Very high	9 march 2015

FG7	Biological data repositories	Company representative	Very high	Supporter	Very high	9 March 2015
FG7	University research institute	Researcher	Very high	Supporter	Very high	9 Marc 2015
FG8	Medical University	Clinician, Researcher	Very high		Very high	9 March 2015
FG9	University medical research institute	Researcher	Very high			9 March 2015

The stakeholders of the BYTE case study are both drivers of the research and affected by the results produced. We will examine their roles in the case study - the extent to which they influence the process of data analytics in the discovery of rare genes - and the inter-relationships between stakeholders. This analysis provides an overview of the logical chain of evidence that supports the stakeholder analysis as GRI is reflective of how certain players in the health data ecosystem can drive differing outcomes.[130]

1.2 ILLUSTRATIVE USER STORIES

The utilisation of big data driven applications in healthcare is relatively mature, although the type of applications and the extent to which they are used vary depending upon the context in which they are applied and the objective of their use. In the context of the BYTE case study on big data in healthcare, the data applications employed are those that facilitate the discovery of new genes and are specific to the process of genetic data analytics. The following stories from the BYTE case study on big data in healthcare provide examples of the usage, objectives and potential stakeholders involved with the health data ecosystem.

- *Research organisation - GRI*

The research organisation acquires genetic data from clinicians who collect data samples (DNA) directly from patients and their immediate family members. However these are usually small in size and are aggregated to produce larger datasets once they have been analysed. The data can potentially be combined with other similar datasets held by other organisations and initiatives on open (or restricted) genetic or medical data repositories. Whilst the primary focus of GRI is the identification of rare genetic diseases, there are other varied potential uses of the data in terms of further public sector projects or by pharmaceutical companies in the production of drug therapies. The research organisation's data usage initiatives can, however, be restricted by the pubic sector funding environment. Also, all European organisations dealing with sensitive personal data are subject to the requirements of the legal framework for data protection, which can be a barrier to reuse of genetic data. Nevertheless, the research organisation facilitates the use of health data in the pursuit of producing positive outcomes, not in the least diagnosing disorders and contributing to findings in medical research.

- *Computational Geneticist/ Bio-mathematician*

A Bio-mathematician or Computational Geneticist is responsible for carrying out the research organisation's data analytics by utilising genetic data specific software, infrastructure and technology processes. A bio-mathematician performs a key role in

[130] "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

meeting the research organisation's objective. The process of data analytics is largely computer driven and heavily reliant on the data applications, analytics tools and specific software. However, the specificity of the tools required means that they come at a great expense to the organisation's budget, leaving the bio-mathematician at the mercy of shared resources and tools. This means that the speed at which data are analysed can be delayed and can be one of the main challenges faced in this role. I3 elaborates on the role of a bio-mathematician: "DNA gets sent to a company and they generate masses of genomic data from that DNA and then I run it through on high performance computing systems."[131] With respect to the volume of data processed, I3 adds:

> I receive the data […] we would work with batches of up to about 100 samples. And each sample generates […] about 10 GB of data per sample. So we are looking at about […] a terabyte of data maybe, so that's the kind of volume of data that were processing. As for quality we have quality controls, so we can […] visualise how good the data is using some software.[132]

- *Translational medicine specialists*

Whilst the primary goal of the organisation's initiative is to identify rare genes, there is also a focus on translating research results into real benefits for patients foremost, and society at large, by contributing to medical research and through the development of treatments and/ or improved diagnostic testing, for example. In the long term, genetic data research is also useful in the context of Pharmacogenomics, a strand of which is to develop personalised medicine. Personalised medicine supports specific administration of drug therapies that accord with the patient's unique drug metabolism. This is a complex process and is in its initial stages of adoption in the UK, where the BYTE case study is based. I4 explains the process of utilising genetic data for this purpose:

> Looking at the variants of genes that are relevant to drug metabolism for example… and work out whether the patient is going to be responding to a particular drug or not…but still very much working with the [GRI] data because that is the source of data […].[133]

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

2.1 DATA SOURCES

The focus of the case study is a publicly funded research initiative with the primary objective of identifying rare genetic diseases. As such, the primary data source is the afflicted patient, and their immediate family members. DNA samples are collected from patients and immediate family members by their primary clinician. This is ordinarily a straightforward and routine process of blood collection:

> when they see the family blood gets taken, and it gets stored in the regional genetics laboratory, so this is sort of the NHS laboratory, they extract the DNA and they keep a copy of it and it gets an ID number.[134]

Individual samples of genetic data acquired through a blood/ DNA test are not generally considered big data. With reference to the volume of the data from each DNA sample: "it is

[131] I3, Interview Transcript, 14 January 2015.
[132] I3, Interview Transcript, 14 January 2015.
[133] I4, Interview Transcript, 18 January 2015.
[134] I1, Interview Transcript, 10 December 2015.

normally expected for each person to have around about between 15 and 20 gigabytes of data comes back and that's your raw data."[135] The raw data is returned in reverse format, to be sequenced in two directions. However, individual samples are commonly aggregated with other data samples to form what is considered big data. The total volume of data collected and aggregated from patients and their family members is estimated to be:

> we have got quite a sizable number of terabytes worth of data sitting on our server […] I think 20 terabytes, but I don't know if it's […] we have got 600 files so if each file is about works out about 40 gigabytes, and 600 times 4 […]and when we do the analysis we tend to run some kind of programmes and look at the data quality and coverage and give us a statistics that go about some sort of QC statistics with the actual raw data in.[136]

A subsequent source of data is genetic data repositories or other datasets held by related medical institutions and/ or within the university to which GRI is linked. However, access to these repositories would form part of additional research by analysing GRI's newly acquired data against data already held in these repositories to eliminate rare genes and genetic mutations. It is only genetic data that is useful in this context as it enables the GRI clinicians to compare their data against similar data when looking to detect genetic mutations or rare genes that have not been identified by themselves or other related projects. Beyond the context of GRI, big health data is increasingly held on open data repositories for use and re-use largely for scientific research purposes, although GRI do not currently access them, especially when a 'trade' of data is required. This is because GRI data use and re-use is subject to the terms of consent agreed to at the initial point of data collection, and because the primary focus is rare gene discovery. GRI data scientists and clinicians require specific genetic data that they collect themselves or compare with data already collected and stored in-house.

2.2 DATA USES

The main focus at GRI is the identification of rare genes, which is facilitated by biomathematics pipeline. This pipeline describes the process of data analytics at GRI, from collection to gene identification.[137]

The data are used for sequencing in the first instance. The data are then analysed by comparison to previously identified genes, and then, results are produced in terms of either finding a genetic mutation or the discovery of an unidentified gene. The results are relayed to the primary clinician who discusses the diagnosis with the patient. Potential subsequent uses in the context of GRI include further research into rare genetic disorders, as well as in the context of translational medicine to produce outcomes that assist the patient. An emerging area of research at GRI is conducting retrospective studies that determine whether clinical decisions would have been made differently had they new information, so that they are made differently in future.

Again, outside of GRI, there are a myriad of potential uses for big data in healthcare, particularly in the commercial context of developing new drug therapies in collaboration with pharmaceutical companies, or modifying or personalising insurance policies.[138] GRI however, focuses its uses in line with its primary mission of rare gene identification and the provision of treatment and genetic counselling. Other re-uses of the data, particularly

[135] I1, Interview Transcript, 10 December 2014.
[136] I1, Interview Transcript, 10 December 2014.
[137] I2, Interview Transcript, 8 January 2015.
[138] FG5-FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

monetising the data is not a primary goal of GRI, although it is a possibility and a focus of other stakeholders, such as pharmaceutical companies.[139]

2.3 DATA FLOWS

GRI personnel undertake all the necessary work from data acquisition, QC preparation, dispatch to whichever outsourced company is decided upon ensuring that the data is returned and downloaded, analysed and stored securely. The flow of data in the context of the BYTE case study on big data in health care involves a number of phases.

In the first phase, genetic data samples are collected from consenting patients who are suspected of having a rare disease. The data are collected for this research once all other avenues of diagnostic testing have been exhausted. Some quality control measures are applied to the raw data are this stage of the process.

The next phase involves sequencing the data. The data samples are sent to a genetic sequencing lab outside of Europe, in this case, Hong Kong, in accordance with patient consent. This occurs once GRI has acquired at least 24 samples. Sequencing the genetic data collected by GRI usually undergoes the following form:

> By far the most common one at the moment is what we call XM sequencing. So that is that you have human gene and more the DNA inside you, is basically is about 3 billion base pairs. But only 1% of it actually codes for the proteins. And we know that in rare diseases over 80% odd of them are caused by mutations that occur in the code sequence […] So the samples get sent away, it normally takes about 2 months for the sequencing to be preformed, to produce the raw data.[140]

Once the data are sequenced, the data, together with the results of the sequencing are returned to the organisation for analysis. Roughly between 15 and 20 gigabytes of raw data per sample are returned on a hard drive and put through an analysis pipeline that involves the following steps that map the data back to the human genome to look for mutations or variants within the dataset. I1 elaborates:

> So your raw data then gets put into an analysis pipeline that we have here. And there are a number of steps, which is mapping it back to the human genome and looking for mutations or variants within that data set. And you produce after a number of these steps a file that is called a Bam file […] I should say the raw data comes in a form in a reverse format […] So you sequence in two directions, so your DNA is double stranded. So basically you take a chunk of DNA and you start at point A and you sequence say 100 base pairs towards point B and then you start at point B and you basically sequence 100 base pairs towards point A. And that fragment is say, 300 base pairs long. So there is maybe 100 base pairs in […] so effectively originally your raw data comes in the form of what fast Q files, and each one of those would be say 10 gigabytes each, so that gives you 20 gigabytes. And then when you have done all this transformation and recalibration and all this fancy work goes onto sort of the removal of the artefacts, you are left with a file that's around about again 20 gigabytes. But it's combined into one file. And then for the majority of the work that we use, we use a file that's called a VCF, which is variants file. And effectively what we are looking for, we are looking for variants in the DNA compared, so where your DNA differs from the population norm.[141]

[139] "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[140] I1, Interview Transcript, 10 December 2015.
[141] I1, Interview Transcript, 10 December 2015.

The data is processed by clinicians and then genome analysts who filter the data and look at variations in the following process:

> you will have the sample sequence aligned against a reference sequences and then we would checked whether there are any differences in the patient's sequence to the reference sequence. So those differences points up either just normal variations that we all have but in our case we are hopefully finding mutations that might caused the disorder that the patient has, if you see what I mean.[142]

This step involves specific software and tools that increase the quality of the data.

Once the analysis has been undertaken, a rare gene is either identified or there is no such result. As the research is not what is referred to as accredited then the GRI team then collaborate with the NHS accredited diagnostic laboratories who will repeat the test and validate the finding in a clinically relevant report. This last step is necessary to achieve validation and subsequent recognition of the findings.

Findings are then referred to the treating clinicians who will then liaise directly with the patient and provide or arrange for the provision of genetic counselling.

The data are stored on an internal and secure database. It is uncommon for the data to be accessed for purposes other than the original purpose of collection, and/ or only in accordance with the data subjects' consent to the use of their data for additional research, and in time, for aggregation with other data sets via health data (open or otherwise) repositories. However, the latter has not been routine practice at GRI as it was initially considered outside the scope of the research.

2.4 MAIN TECHNICAL CHALLENGES

GRI utilises roughly three main technologies.[143] These technologies are designed specifically for the analysis of genetic data and biomathematics. This means that, generally speaking, the number of technological challenges are minimised. The challenges addressed below arise in the context of GRI, although there are overriding challenges that were identified at the BYTE Focus Group on big data in healthcare that may be present industry wide.[144]

Data acquisition
During the first phase of data collection, GRI does not experience any technology related barriers as their data consists of DNA samples, which are acquired through traditional blood testing techniques. However, GRI experienced an issue with capacity and storage when the volume of data it acquired increased. This is discussed below.

Data curation, analytics and storage
Data processing at GRI is computer intensive, which raises a number of technical challenges. With respect to data curation, analytics and storage, the main challenge faced by GRI personnel was ensuring the data remained anonymised. GRI programmers developed a database that supports data anonymisation, as well as data security for use by the GRI team.

---

[142] I3, Interview Transcript, 14 January 2015.
[143] I2, Interview Transcript, 8 January 2015.
[144] For example, traditional approaches to recording health data do not support a search function, and health data is often used for the sole purpose of its collection. However, technology to facilitate dual-usage is currently being developed: "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

In terms of data curation, GRI utilises bio-mathematicians and computer programmers to develop additional databases to meet challenges as they arise. This is an evolving practice as the volume of data held by GRI continues to increase. However, the challenges are minimised somewhat by the fact that GRI deals only with genetic data, and challenges that do arise are more commonly associated with the access to technologies that are limited in line with resource availability. However, one challenge faced by GRI was making the data interoperable across all its databases and some eternal databases. The current system facilitates the dumping of the data, 5000 or 6000 exomes (part of the genome), in a single server or multiple servers so that they may be called up at a later stage, as well hyperlinking the data across all GRI databases. This met challenges faced by GRI with respect to interoperability.

Other challenges faced by GRI related to identifying data samples in a systematic way. The internal response was to develop a code for each sample that linked it to the project and the individual from each family structure without enabling identification of the patient. This Laboratory Information Management System (LIM System) and its relational database provide an identifier for each sample, together wit relevant technological information, such as the sample concentration and when the sample was sent for sequencing. GRI works with an internal database of approximately 450 samples, but the LIM System allows clinicians and data scientists to look on public databases for the frequency of their variants.[145] The issues of anonymisation and data security remain relevant throughout all phases of data handling.

Another challenge for the GRI team is gaining access to technologies as the data analysis is computer intensive. However, this challenge is linked largely to a lack of resources. A GRI biomathematician explains:

> The main challenge I have is computing resources because if you imagine […] so when I said say one sample is 10 GB, analysing it requires about 100 GB of space. And then I may have 100 samples, so we do use a lot of computing resources and we are collaborating with the computer science department […] it is just is just hundreds and hundreds of what you think of as computers […] all in one room and they're all interlinked. So it makes it like a supercomputer and so then we have access to that but a lot of people do because they share it […] but everyone who is using the resources get put into a queue. It is a big powerful resource and it is the only way we could do the research. But sometimes you do get stuck in a queue for a while, that's my main hold up.[146]

Thus, this technical challenge is a result of restricted access to technologies resulting from the limited resources.

Ultimately, the technical challenges faced by GRI have led to innovative solutions. These solutions reflect a positive eternality of health data utilisation by this research initiative, and are also addressed as an economic eternality below.

2.5 BIG DATA ASSESSMENT

The utilisation of big data in healthcare per se is maturing (including, structured, unstructured and coded datasets), and the employment of big data technologies and practices are becoming more widespread. Genetic data handled by GRI, makes up just a small percentage of health

[145] I1, Interview Transcript, 10 December 2014.
[146] I3, Interview Transcript, 14 January 2015.

data generally, in fact raw genetic data accounts for approximately 5% of the big data utilised.[147] However, there are vast amounts of health data generated, used and stored by stakeholders in the healthcare sector per se, including the data held in human data repositories or by health insurance companies for example.[148] Despite increasing volumes of big health data, individual samples of genetic data do not necessarily contend with the Gartner definition of big data until they are aggregated with other samples. For example, in the first instance, data sample sizes are in batches of up to about 100 samples, with each sample generating about 10 GB to 20GB of data on a BAM file. However, the amount of aggregated data is approximately one terabyte of data, which is more in line with 'big' data volume, and becomes even bigger when combined with other reference datasets[149]. Big health data in the context of GRI lies in combining smaller datasets to create larger datasets, and the potential benefits that flow from this aggregation. Nevertheless, health data generally is considered to represent big data in terms of its volume, variety and velocity.[150]

In terms of the velocity of the data utilised by GRI, the time is takes to process involves the timing of two fundamental steps in the process, namely the sequencing of the data and the data analyses. Sequencing of individual samples takes up to two months, whilst the in-house analytics process takes 1 to 2 weeks. However, the practical reality of sharing resources means that the analyses of the data samples can take up to 4 weeks. The time involved in this process is subject to the availability of computing resources.[151] Irrespective of the resource constraints, the velocity of genetic data being that it is computer and time intensive indicates that it conforms to the commonly accepted definition of big data.

The element of variety of the data was found to be negligible in the BYTE case study as GRI focuses on one type of data, namely genetic data collected for a specific purpose. Whilst the DNA sample potentially provides a wealth of information about each data subject, it is one type of health data. The GRI team have it sequenced undertake data analytics for the sole purpose of gene identification. Nevertheless, on a larger scale, the variety of health data available across the industry is incredibly varied and in this context constitutes big data.

Overall, whilst the data utilised by the case study organisation represents just one type of health data, the aggregation of the data samples, the time it takes to sequence and analyse it, and the application of data specific tools and technologies provide insight into a live example of big data utilisation in the public health sector.

3 ANALYSIS OF SOCIETAL EXTERNALITIES

Big data in healthcare produces a number of societal externalities, which in part are linked to the inevitability of issues that arise in relation to the utilisation of big health data, which is highly sensitive in nature. Externalities can be generally categorised as economic, social and ethical, legal or political – see the list in Table 55. They can be positive or negative or both. The BYTE case study on big data reflects externalities that are specific to that data driven initiative examined. However, there arise other externalities in relation to the utilisation of big data in healthcare generally that were identified at the BYTE Focus Group on big data in healthcare.

[147] FG5 – FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[148] FG5 – FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[149] However, GRI combines its data with internal reference datasets only.
[150] FG5 – FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[151] I3, Interview Transcript, 14 January 2015.

3.1 ECONOMICAL EXTERNALITIES

There are a number of economic externalities associated with the use of big data in healthcare. One important result is cost saving for healthcare organisations that are gained through more accurate and timely diagnoses and efficient treatments. This also means that resources can be allocated more effectively. This is particularly important when dealing with rare genetic disorders that may not otherwise attract the attention that disorders and health issues affecting the wider population do. Where GRI is concerned, it can result in more time for the patient to experiment with treatment and drug therapies who may otherwise pass sooner.

In addition, the utilisation of big data in healthcare produces another economic externality in that it potentially generates revenue especially through the development of marketable treatments and therapies, and the innovation of health data technologies and tools. Data driven innovation is constantly occurring. For example, a translational medicine specialist suggests database development:

> one of the things that we've been working on here is trying to develop a database of possible deletions or duplications. And if they are of interest we would then follow up and try and confirm whether they are real because the software and the data doesn't allow that, if you see what I mean […] as soon as we are confident that we have found something that would be helpful, we would publish it and make it available definitely.[152]

Other innovative ways for creating commercial value (and adding social value) are also suggested:

> if you're going to make the most of all of those data you need to be engaging industry and creating a whole new industry actually, which has started to happen in this country. I found that sort of an analysis company for the next generation sequence which is going to help analyse this 100K Genomes data as they come online with some colleagues up in […]. And so we are using exactly the same principles as we initially laid down for GRI so yeah that's working out well.[153]

Furthermore, GRI utilises a specific sequencing laboratory in Hong Kong. This specialist laboratory is an example of a business model focused on generating profit through specialised big data practices, in particular genomic sequencing. This business model is an example of an economic externality produced by the utilisation of big data in healthcare. Furthermore, GRI employ the specialist laboratory in Hong Kong because there is not an equivalent European competitor. This indicates a gap in the European market, which can be addressed by relevant stakeholders or indeed a public/ private sector collaboration to meet this demand. This is linked to innovation, which is another positive economic externality produced by the utilisation of big data in healthcare. GRI provides a number of technological innovations in terms specifically designed tools and software to meet the technical challenges it has faced. One such example is the development of tools to assist with reporting processes.[154] Other examples are identified above under the section on technical challenges.

[152] I3, Interview Transcript, 14 January 2015.
[153] I2, Interview Transcript, 8 January 2015.
[154] I2, Interview Transcript, 8 January 2015.

Despite the positive economic impacts of big data utilisation in healthcare, research initiatives, such as GRI that are publicly funded, are naturally subject to financial restrictions and cost savings measures implemented by governments. This can be a hindrance to progress. For example, GRI share the computing infrastructure with a department at UCL, and this means that processing can be delayed from taking roughly 1.5 weeks with private equipment to a 4 week time period when sharing computer resources.[155] This represents both a technical challenge and a negative economic externality for GRI. However, the GRI model could potentially be funded by collaborations with private sector stakeholders, who could also repurpose the data for commercially driven purposes. This could entail patenting new technologies and tools for anonymised and secure genetic data analytics, as well as collaborations for the development of drug therapies. However, as mentioned previously, GRI's primary focus is gene identification and commercially driven models are not yet in place. This however remains a potential area for development within GRI. Nevertheless, GRI contributes through potential cost savings in healthcare and by making a valuable social contribution that cannot be measured in the traditional economic sense.

Table 37 Economical externalities in the healthcare case study

Code	Quote/Statement [source]	Finding
E-PC-BM-2	If you're going to make the most of all of those data you need to be engaging industry and creating a whole new industry actually, which has started to happen in this country. I found that sort of an analysis company for the next generation sequence which is going to help analyse this 100K Genomes data as they come online with some colleagues up in the Sanger Institute in Cambridge. And so we are using exactly the same principles as we initially laid down for GRI so yeah that's working out well.[156]	There are economic opportunities and costs savings linked to innovative approaches to data usage in healthcare, especially in the development of future treatments, including personalised medicine. This will also result from collaborations between public sector and private sector organisations.
E-PO-BM-2	One area for development as a potential business opportunity is deal with the challenge of interoperability of big health data.[157]	The situation beyond GRI is that similar technology related challenges arise and require address. The means by which these challenges can be addressed are often gaps in the market for innovative business models and the development of tools that achieve commercial viability for innovators.

[155] I3, Interview Transcript, 14 January 2015.
[156] I2, interview Transcript, 8 January 2015.
[157] FG5 – FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

3.2 SOCIAL & ETHICAL EXTERNALITIES

Social

There are a number of positive social externalities that are a direct result of big data in healthcare. GRI provides examples of these. The identification of rare genetic disorders provides treatment opportunities for the patient, as well as more effective diagnostic testing for future patients and a greater understanding of rare genetic disorders generally. In addition, analyses of genetic data enables treating clinicians to provide a range of other healthcare services for family members, including genetic counselling and assisting parents of the affected (child) with natal counselling and carrier testing, as well as assisting in identifying genetic metabolic conditions. Without this sort of data analytics, therapeutic remedies may not be identified and administered. For example, in the case of a patient who travels to London to take part in GRI research, they will receive the following treatment benefits:

> So we will liaise with the local regional genetics team and get them to be seen by a clinical genetics or counsellor up there, who will then take them through the report and say look we have made this diagnosis. This is the implication of having this disease and this is what we think in the way of prognosis and then we also can provide things such as prenatal testing from that, gene discovery. We can provide carrier testing for other at risk members in the family. And in some cases, sort of sometimes metabolic conditions, you can fairly quickly identify possible therapeutic remedies for those patients […] Then those will be the immediate benefits I would say […].[158]

Beyond the initial purpose for the data collection, there is limited or no re-use of that data currently This mainly due to the legal and ethical issues raised by that re-use and because GRI's primary focus is patent care through rare gene identification. Furthermore, GRI's re-use of the genetic data is restricted to the extent to which data subjects (patients and family members) have consented to it. To date, re-use of genetic data held by GRI has extended to further research of rare genes it has identified that has involved:

> you can usually find someone across a very large organisation who might have an interest in the gene that is discovered for a disease. So then you may be able to entice that particular research group to be able to take it further or they might already have a project going forward on that particular gene […] So what I'm saying is that it doesn't just stop at gene identification it goes right the way through to some kind of functional investigation, further functional investigation with a view of being able to understand what does that gene do.[159]

However, data re-use may become a stronger focus in the future, which is supported by GRI's broadening consent policy[160] for the purpose of producing additional benefits for patients and society. There will likely be an increase in focus on research for the purpose of developing personalised medicine treatments, which focuses on improved treatment based on patient drug metabolism. The potential social (and economic) externality associated with this is the development of new therapies and (cost-effective) efficient approaches developed and implemented by clinicians, medical researchers and pharmaceutical companies that have the potential to reach a broader patient network, and aid the health of society at large. Nevertheless, whilst the positive social impacts of re-using data held by GRI are obvious, ethical considerations will remain at the forefront of any policies supporting the repurposing of genetic data, especially as it is sensitive personal data.

---

[158] I1, Interview Transcript, 10 December 2014.
[159] I2, Interview Transcript, 8 January 2015.
[160] I2, Interview Transcript, 8 January 2015.

Beyond the context of GRI, participants at the BYTE Focus Group on big data in healthcare identified a number of positive social externalities, including: better decision-making; improved knowledge sharing; the identification of good medical practices; and the combining of different health data to produce a positive social impact. Nevertheless, the utilisation of big data in healthcare is thought to potentially produce a number of negative externalities as well, although these were not a product of the GRI component of the case study. Potential negative externalities linked to the utilisation of big data in healthcare include: the over-medicalization of an otherwise healthy population; and/or discrimination based on the stratification on genotype or in relation to health insurance policies. [161]

Table 38 Social externalities in the healthcare case study

E-PC-TEC-1	[…] we are collaborating with another researcher and he is trying to build a big database based on the genomic data that we have […] and it may help connect clinicians and improve their understanding of inherited disorders as well.[162]	The sharing of big health data assists in understanding rare genetic disorders, which in turn, provides members of society with an increased understanding and potential treatment.
E-PC-BM-2	[…] it's about really being able to understand far greater what the functional consequences of mutation are. And then what can we do to try and alleviate those problems. And the idea is one, can you develop treatments to help treat that to alleviate the symptoms to some degree. And ultimately can you then find something…some sort of gene transfer or some kind of technology where you can actually alleviate prevent the disease from occurring in the very first place […] So if you can find a diagnosis and you get it much earlier, the earlier you can get it, the earlier you can start treatments. And hopefully by doing that, a lot of times you can prevent a number of these diseases from occurring.[163]	The social impact of GRI's utilisation of big health data is an overwhelming externality of the case study.
E-PC-BM-2	Big health data will lead to be better informed decision making that will have a positive impact on citizens' treatments and overall health care. Being able to analyse all health data from different sources will enable the identification of "good" medical practices and decision-making processes that can be adopted by other professionals.[164]	Big data will, in general, have a positive impact on the entire health care system.

Ethical

Ethical externalities are largely associated with issues pertaining to patient (and family member) privacy, and the discovery of incidental findings, especially when these findings are negative. These concerns are purportedly addressed by the terms of consent contained within the GRI consent form. However, anonymity cannot be guaranteed because, "practically

[161] FG5-9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[162] I3, Interview Transcript, 14 January 2015.
[163] I3, Interview Transcript, 14 January 2015.
[164] FG5 – FG9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

speaking and irrespective of the anonymisation processes involved, patients are, by the rarity of the disease, more likely to be identifiable."[165] The extent of the terms to which consent is required has broadened over time because potential uses of data are ever evolving in line with technological developments. However, there remains contention surrounding the potential breadth of the consent form insofar as the inequality of the parties consenting. It is feared that patients and their family members are likely to consent to any terms for re-use of their data because it is difficult for them to otherwise fund the extensive analytics or gain assistance with their disorder.

Incidental findings are another ethical externality related to GRI research. Incidental findings are the health issues (unrelated to the purpose of the testing) that are discovered when data is analysed. For example, cancer genes may be discovered alongside the identification of rare genes or other genetic mutations. Whilst this is covered in the GRI consent form, the findings remain a source of contention between researchers and clinicians. The latter generally insist on not relaying these incidental findings to the patient and their family members, which represents an ethical dilemma. Incidental and non-promising findings were raised as a negative externality on the utilisation of big data in healthcare at the BYTE Focus Group. Participants discussed this in the context of how "non-promising" findings should be dealt with as it presents an increasingly relevant ethical dilemma for researchers and clinicians.[166] This remains a real issue for select stakeholders – patients, clinicians and researchers. However, with the example of GRI, the work carried out by that organization is subject to vigorous ethical controls implemented by the academic institution it is connected to. These guidelines are specifically designed to respond to ethical questions that arise in relation to use and re-use of sensitive personal data. Furthermore, GRI's research is monitored by a research ethics committee and from whom GRI requires ongoing ethical approval for gene discovery and consent.

Table 39 Ethical externalities in the healthcare case study

Code	Quote/Statement [source]	Finding
E-OC-ETH-10	Data are going to be held on a database here and we may use that data anonymously for quality control, for improving our pipeline, our software and that sort of thing. So we get patients to sign that obviously. We have now added in recently another clause, which says the patients […] we may even be working with industry on this. Because it maybe that a commercial outfit want to develop a companion diagnostic tool or even therapies based on the information that we get from their genome or their external data.[167]	The issue of consent broadens in line with potential uses opened up by emerging technologies.
E-OC-ETH-2	It's a strange scenario because what you find in all the research that tends to happen is that the patients are very much of the thought process that it's their data. It's their data so you give them back their data or you tell them about it. And if there is something there, then they want to know […] it's really strange bizarre scenario because the people who are most against it, are […] the people who actually work with the patients […].[168]	Incidental findings have been a longstanding issue of contention between clinicians because it raises important ethical questions.

[165] I2, Interview Transcript, 8 January 2015.
[166] FG5-9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[167] I2, Interview Transcript, 8 January 2015.
[168] I1, Interview Transcript, 10 December 2014.

E-OC-ETH-2	So in our own consent we never say that data will be fully anonymous. We do everything in our power so that it is deposited in a anonymous fashion and again this part of our governance where you only have two or three at the most designated code breakers if you like who have actually have access to that married up information. But having said that the patient […] when we consent we are very careful in saying look it's very unlikely that anyone is going to actively identify information about you […].[169]	Given the rarity of diseases and genetic disorders being identified, it is impossible to assure anonymity.

3.3 LEGAL EXTERNALITIES

Health data is by its very nature sensitive data and defined as sensitive personal data under the European data protection framework and thereby implicating a number of related issues. The data subjects are primarily children, which means valid and informed consent is required from their parent/s or guardian/s. This issue can be compounded in light of the extent of consent required. For example, consent is not only required in relation to the initial collection of data, but is required for all subsequent use and handling, as well as foreseeable outcomes, such as incidental findings.

A major issue that produces legal externalities is data anonymisation. Anonymisation is a legal requirement. GRI personnel have developed an internal database to ensure anonymisation. More generally in relation to the data protection compliance, a GRI geneticist observes:

> it's something that becomes second place really in laboratories now […] But so we will have an ID for the sample that gets sent away and that's normally just the sequential list of…so we sent out stuff to BGI, so it goes from BGI 1 to BGI 300 now. And then that has got no relevance to the sample itself and they are all different. The data itself when it comes back is all on hard drives which goes into a locked storage cabinet […].[170]

The issue of data protection and information privacy is at he forefront of the minds of those handling sensitive personal data at GRI:

> as it is patient data we are very careful with it. It is kept in a secure locked place, there is no access to this data apart from me and from people in my office. The data itself, the names of the files or whatever bear no relationship whatsoever with the names of the patients. Those kinds of systems of security are in place, if you see what I mean.[171]

These issues call for the development of adequate protections that balance the right to personal data protection whilst fostering innovation in the digital economy. In that regard, participants at the BYTE Focus Group on big data in health care observed:

> Big data demands the development of new legal frameworks in order to address externalities such as discrimination, privacy and also enhance and formalise how to share data among countries for improving research and healthcare assistance.[172]

[169] I2, Interview Transcript, 8 January 2015.
[170] I1, Interview Transcript, 10 December 2014.
[171] I1, Interview Transcript, 10 December 2014.
[172] FG5-9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

Although the necessity of improved legal frameworks was initially viewed as a negative externality, it can also be seen as a positive externality associated with big health data as it illuminates the potential of data sharing in the healthcare sector.

Data security preservation is also routinely adhered by building security enhancing mechanisms into the software and tools implemented. What this means, is that the technology has been developed in accordance with the relevant legal requirements. Furthermore, the genetic data held by GRI is 'under lock and key', which entails "passwords and encryption and there is a physical and hard drives, external hard drives that are also under lock and key as well."[173] Data security and anonymisation are also overseen by a departmental data protection officer. Subsequent use of the data is also heavily monitored, even in the case of anonymisation. For example, if GRI would want to contribute their research data to an open data repository for further research, the GRI team would need to apply for, and be granted approval of this. Although these measures ensure compliance with standard data protection requirements, they can also hinder further research, which in turn, could lead to new developments and treatments. For example, at this stage, the data held by GRI is entered onto internal databases only to minimise any potential liability. However, this means that the data is not available for re-use by other experts or researchers who could potentially utilise the data for medical progress.

Lastly, threats to intellectual property rights can arise in relation to subsequent uses of big health data, such as in relation gene patenting (and licensing) of new drug therapies, or if it were to be included in works protected by copyright. Additional concerns that arise in relation to big health data are data hosting and reproducing copies of the data. These are not currently relevant to the work undertaken by GRI as they are outside the initiative's objectives of rare gene identification for patient care and treatment. They are however topical in relation to big health data generally, as observed by participants at the BYTE Focus Group on big data in healthcare.

Table 40 Legal externalities in the healthcare case study

Code	Quote/Statement [source]	Finding
E-PC-LEG-4	[…] as it is patient data we are very careful with it. It is kept in a secure locked place, there is no access to this data apart from me and from people in my office. The data itself, the names of the files or whatever bear no relationship whatsoever with the names of the patients. Those kinds of systems of security are in place […].[174]	Anonymity is at the forefront of researchers' minds and the requirements under data protection framework have been fundamental in researchers implementing methods of compliance.
E-PC-LEG-4	They'll have a code that they'll use that's completely anonymous to anyone else […] The ones that come from actually the diagnostic laboratory come with a name and then you need ID. And it's something that obviously for us it's very important that we don't relate the patient details to the actual	Procedures are in place. This is not as big of an issue as previously anticipated, and it

[173] I3, Interview Transcript, 14 January 2015.
[174] I3, Interview Transcript, 14 January 2015.

	sequence data. So it's something that we have being working on for probably about a year now is, we hired a programmer […] all our samples now, we have just finished making it basically have all got a unique identifier that the data that gets sent off to the sequencer, that's just a completely random code, that has no information about the patients. So we always keep the patients and the actual ID of the sample totally separate, they are completely different files. So you couldn't join the two of them up, which is really important.[175]	is an issue at the forefront of research institutes dealing with health data.

3.4 POLITICAL EXTERNALITIES

Political externalities did not arise specifically in relation to GRI, aside from the relationship between partisan priorities and funding that impacted upon access to technologies, as discussed above. However, participants at the BYTE Focus Group on big data in healthcare identified the following relevant political externalities: improved decision making and investments in healthcare were identified as positive political externalities produced by big data utilisation in healthcare; and conversely, the need to develop policies addressing potential discrimination following the use of big health data was identified as a negative externality.[176]

Table 41 Political externalities in the healthcare case study

Code	Quote/Statement [source]	Finding
E-PP-LEG-3	The availability of big amounts of data will enable politicians to have more information about different situations in the health sector and thus a better understanding that may lead to improve their decision-making and increases the investments in healthcare. [177]	Healthcare is an important political issue.

4 CONCLUSION

The BYTE case study focuses on GRI, which reflects the maturing state of big data utilisation in the public healthcare sector for improved efficiency and accuracy in the provision of preventive, curative and rehabilitative medical services. There exists a myriad of 'types' of health data, although the BYTE case study organisation deals with genetic data only. Data in the form of genetic samples are collected from individual patients and immediate family members, which are later analysed primarily for diagnostic and treatment purposes. In the case of genetic data utilised by GRI, each individual sample is by itself not likely to be considered big data, although the aggregation of data samples requiring big data practices and applications for analyses represents big data as it is conventionally understood.

GRI is an example of when a public sector research initiative can produce societal externalities as a result of big health data utilisation, despite being restricted in the volume and variety of data it deals with. These externalities are produced indirectly to pursuing the primary objectives of rare gene identification for improved diagnoses, patient care and

[175] I1, Interview Transcript, 10 December 2014.
[176] FG5-9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.
[177] FG5-9, "Big Data in Healthcare", *BYTE Focus Group*, London, 9 March 2015.

treatment. The evidence of big health data in practice provided by the GRI case study is supplemented by discussions at the BYTE Focus Group on big data in healthcare.

GRI illuminates the roles played by a number of stakeholders that are vital to the initiative. The case study also enables us to identify the growing list of potential stakeholders involved in big data utilisation across the healthcare sector generally, especially where innovations and new business models can be developed and employed to handle big health data, and where stakeholders can collaborate to pursue other externalities such as drug development.

Overall, this case study highlights a number of positive societal externalities that flow from genetic research and rare gene identification, which is facilitated through the utilisation of big health data. GRI also allows us to witness the potential impacts of a data driven initiative in terms of producing additional and specific economic, political and legal externalities. GRI's utilisation of genetic data also highlights when more controversial impacts can arise, such as in the case of ethical considerations relating to privacy and consent, and legal risks associated with data protection and data security.

Moreover, GRI provides examples of the practical reality of big health data utilisation in the public sector, and the technical challenges that are faced by the GRI team. However, in addition to being challenges, they present opportunities for stakeholders to innovate to address them through the implementation of new business models or by improving tools and technologies implemented for big health data utilisation. The effect of this innovation is likely to be a continual increase in data utilisation across the healthcare sector. This will then translate into real benefits for patients, as has been the case with GRI where improvements in diagnostic testing, genetic discoveries and developments with genetic counselling have been achieved. Beyond the context of the BYTE case study organisation, these benefits can be transferred to society at large through increased understanding of rare genetic disorders and tailored treatments and therapies.

MARITIME TRANSPORTATION CASE STUDY REPORT

Maritime transport is essential to the development of international economic activities, by providing a backbone for the exchange of goods. Despite its importance, the maritime industry does not attract much attention. In this case study, we have interviewed representatives of the majority of the actors in the industry. Based on these interviews we have identified barriers and enablers for adopting data centric services, which in turn were used to identify societal externalities in the Maritime industry. We point out, that this task is very subjective with respect to our background and understanding of the maritime industry. Additionally, due to the vague (i.e., hard to quantify) nature of this task (i.e., identify societal externalities) we could not create a clear mapping between maritime specific externalities and the project-wide predefined externalities. According to our analysis, it seems that externalities caused by data utilisation are very low or non-existing. In addition, the shipping sector regards externalities as very unimportant as long as they do not affect their business.

1 OVERVIEW

The shipping business is essential to the development of economic activities as international trade needs ships to transport cargoes from places of production to places of consumption. Shipping in the 21st century is the safest and most environmentally benign form of commercial transport. Commitment to this principle is assured through a unique regulatory framework adopting the highest practicable, globally acceptable standards that have long pervaded virtually ship construction and all deep sea shipping operations. Shipping is concerned with the transport of cargo between seaports by ships, where it is generally acknowledged that more than 90% of global trade is carried by sea. Despite of shipping's importance to international trade, the maritime industry goes usually unnoticed, due to the following factors:

- **Low visibility:** In most regions, people see trucks, aircraft and trains, but not ships. Worldwide, ships are not the major transportation mode since numerous large organizations operate fleets of trucks and trains, but few operate ships.
- **Less structured planning:** Maritime transportation planning encompasses large variety of operating environments that require customization of decision support systems and makes them more expensive.
- **Uncertainty:** Ships may be delayed due to weather conditions, mechanical problems and strikes (both on board and on shore), and in general, due to economic reasons, very little slack is built into their schedules.

Long tradition and high fragmentation: Ships have been around for thousands of years and therefore the industry is characterized by a relative conservative attitude being reluctant to new ideas. In addition, due to the low barriers to entry there are many small, family owned shipping companies, which are not vertically integrated into other organizations within the supply chain.

We tried to get interviews with the different stakeholders as possible, see Section 1.1. The interviews were mainly telephone conferences typically lasting one hour. An interesting observation is the general, rather negative, attitude of ship owners towards being interviewed about externalities. They consider externalities originating in the use of (big) data as either

unimportant as they do not affect their business in the short term. Ship owners have an investment time horizon (return on investment) of a couple of months maximum.

1.1 IMPORTANT STAKEHOLDERS IN MARITIME INDUSTRY

The supply chain of the shipping business contains a series of actors, playing various roles in facilitating services associated with trade or providing a supporting facet, for instance:

- **Ship-owners:** Parties that own ships and make decisions on how to use existing ships to provide transportation services, when and how to buy new ships and what ships to buy.
- **Shipbuilders:** Parties that build and repair ships and sell them to ship-owners.
- **Classification Societies:** Parties that verify that the ships are built in accordance to their own Class Rules and verifying compliance with international and/or national statutory regulations on behalf of Maritime Administrations.
- **Component Manufacturers:** Parties that produce all pieces of equipment and material for the ship.
- **Marine consultancies:** Parties offering design and superintendence services to ship-owners.
- **Maritime Administrations/Authorities:** Agencies within the governmental structure of states responsible for maritime affairs.
- **Terminal operators:** Parties that provide port services to ships such as berthing and cargo handling.
- **Charterers:** Entities that employ ships to transport cargoes.
- **Shipping Associations:** Entities providing advice, information and promoting fair business practices among its members.

In addition, there is a myriad of actors to make this industry sector functioning, such as fuel provider, crew leasing companies, naval academies, etc. In this cases study we have not interviewed charters, terminal operators, and naval design representatives. Table 42 below provides an overview and a very rough qualitative categorisation of their business with respect to data use.

Table 42: Mapping of organization/s to D8.1: Stakeholder taxonomy

Organization		Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
1	Established Ship Owner	Transport	Laggards	Semi-manual acquisition Usage	Factory role
2	New Ship Owner	Transport	Laggards	Semi-manual Acquisition Usage	Support role
3	European Yard	Manufacturing	Late majority	Usage	Factory role
4	Navigation Equipment Supplier	Manufacturing	Late majority	Acquisition Analysis Usage	Strategic role
5	Machinery sub-system Supplier	Manufacturing	Early majority	Acquisition Analysis Curation Storage Usage	Strategic role
6	Shipping Association	Transport	Late majority	Usage	Support role

7	Maritime Consulting Company	Transport	Early adopter	Analysis Usage	Turnaround role
8	Classification Society	Transport / Legal	Early majority	Acquisition Analysis Curation Storage Usage	Strategic role
9	Natl. Coastal Authority	Legal	Early adopter	Acquisition Storage Usage	Turnaround role

Table 43 provides the identification of the various actors that were interviewed and the knowledge of the interviewee.

Table 43: Profiles of the interviewees of the case study, according to Deliverable D8.1: Stakeholder taxonomy

Interviewee	Organization	Date	Knowledge	Position	Interest
1	Established Ship Owner	18/03/2015	Very high	Senior Business Manager	Low
2	New Ship Owner	09/03/2015	Very high	Senior Technical Manager	Low
3	European Yard	18/02/2015	Very high	Senior Technical Manager	Average
4	Navigation Equipment Supplier	17/02/2015	Very high	Senior Business Manager	Very high
5	Machinery sub-system Supplier	21/11/2014	Very high	Senior Technical Manager	Very high
6	Shipping Association	05/03/2015	Very high	Senior Technical Manager	Low
7	Maritime Consulting Company	12/03/2015	Very high	Senior Business Manager	High
8	Class Society	15/10/2014	Very high	Senior Academic	Very high
9	Natl. Coastal Authority	11/02/2015	Very high	Senior Technical Manager	Very high
10	Maritime focus group	17/04/2015	Very high	NA	Very high

1.2 ILLUSTRATIVE USER STORIES

The utilisation of (big) data driven applications in shipping varies largely dependent on the different maritime actors. The following stories are representative illustrations about generally encountered opinions:

- **Ship-owners**. The main interest of ship owners is to provide competitive transportation offerings. Data they need for their daily operations is therefore on a quite aggregated level, i.e. fuel consumption, emission reporting, arrival scheduling etc. The ship crew is responsible for smaller maintenance tasks, optimization and handling of the ship. The needs for data handling cannot therefore fall under 'Big Data'; additionally data collection is performed manually into forms, i.e., noon reports. Few companies have established pilot cases and then only on a small fraction of their fleet to investigate automatic collection of aggregated data.

- **Shipping Associations**. They do not have big data, nor are they keen on obtaining it. Their focus is on information sharing (on an aggregated level) and on contractual and commercial arrangements. Their concern is also on potential misuse of that data through industrial espionage.

- **Administrations/Authorities**. Coastal authorities are mainly interested in aggregated data from ships such as environmental pollution, info about cargo, and data that is used by customs authorities. These data originate from the vessels noon reporting of manual reporting when entering national waters. Over the last years, an automatic ship identification transmitter (AIS) has become mandatory for all vessels above 300 GT. Data about position, speed, heading, etc., are automatically transmitted to land depending on the ships speed, i.e. between 2 sec and 30 sec. These data are used by the vessel traffic systems in traffic surveillance and control. AIS data is aggregated, i.e., on a 6 min or 10 min time basis, and made available to the public.

- **Consultancy**. Shipping contracts are used to get an indication of how cheap/expensive a particular shipment is. Container pricing benchmarking service has had a significant impact on the container shipping market and it makes suddenly the pricing structure transparent and globally available. Therefore, some of the large price fluctuation has been smoothed out.

2 DATA SOURCES AND TECHNICAL CHALLENGES

2.1 DATA SOURCES

During the interviews, we identified the following data sources and their usage:

- **AIS**. An AIS transponder on board automatically transmits data about a) position, course, speed, b) identity, vessel type, dimensions and c) destination, estimated time of arrival, cargo, draught to appropriately equipped shore stations, other ships and aircrafts[178]. The data exchange rate depends on the vessel's speed and ranges between 1 message per second to 1 message per 0.5 minutes.
- **Emission** data shall, according to MARPOL Annex VI (1997), be recorded and reported to national authorities when within ECAs (Environmental Control Areas). Emission data are sulphur oxides (So), nitrous oxides (NOx), ozone depleting substances (ODS)[179]. Other emission could encompass information about anti-fouling, ballast water, incineration, sewage or garbage disposal.
- **Operational (ship)**. This data are utilised in evaluating the performance of the ship with respect to GPS position, speed, heading, engine power, fuel consumption (during transit and at port), environmental forces including weather conditions, as well as other voyage information and are referred to as "noon reports".
- **Operational (sub-system)**. This data concerns parameters (i.e. propeller rpm[180], engine temperature, combustion pressure, navigational data, fuel consumption[181] electricity produced, etc.) regarding the operation of any particular sub-system on-

[178] http://en.wikipedia.org/wiki/Automatic_Identification_System
[179] http://www.imo.org/OurWork/Environment/PollutionPrevention/AirPollution/Pages/Default.aspx
[180] http://www.km.kongsberg.com/ks/web/nokbg0240.nsf/AllWeb/ECC998CE82FE3801C125758300448E97?OpenDocument
[181] http://www.verifavia.com/bases/ressource_pdf/178/CE-Delft-Monitoring-of-bunker-fuel-consumption-1-.pdf

board, i.e. lubrication system, water cooling system, starting air system, ballast water pumps/piping system, etc.

- **Ship design**. It is a comprehensive set of information consisting of ship hull, subsystems/product data and its blocks, sections, all structural elements, materials used, systems and equipment installed on-board.

It should be emphasised that most of the data streams mentioned during the interviews are proprietary, i.e. use private data formats (= not open), except for the AIS data which are an ISO standard. The reasons for using proprietary data formats are entirely business related, ranging from forcing customers to buy software, achieving customer lock-in, avoid that others can use the data, hinder re-engineering, or simply to protect the data and/or data the generating mechanism as much as possible.

Table 44 shows the main data sources mentioned in the interviews and their originally usage. The externalities identified in this case study is based on this original usage.

Table 44: Data sources properties and the originally intended usage in the maritime industry

	Org. ID	Data Source	Data usage	Acquisition	Storage	Access	Data size at collection point
a	7,8, 9	**AIS**	Mainly for navigation aid	Automatic	Centrally	Public (aggregated only)	~GB/day
b	1,2, 7,9	**Emission**	Legal requirements on emission reporting	(semi-) Manual	Centrally	Public (aggregated only)	~kB/day
c	1,2, 7,8, 9	**Operational (ship)**	Control and operation of ship	(semi-) Manual	Distributed	Private (aggregated only)	~kB-~GB/day
d	4,5	**Operational (sub-system)**	Control and operation of ship machinery	(semi-) Manual / Automated	Distributed	Private (aggregated only) Raw	~kB/day ~MB-~GB/day
e	1,2, 3,7, 8,9	**Ship design**	Legal requirements, Construction purpose	(semi-) Manual / Automated	Distributed	Private (aggregated only)	~MB

2.2 DATA USAGE

In the following the originally intended use of the various (groups) of data sources are described. It should be pointed out that other uses often have evolved as a consequence of availability of data.

a. AIS data as a navigational aid:
The original purpose of AIS (Automatic Identification System) was to assist a vessel's watchstanding officers and allow maritime authorities to track and monitor vessel movements. It was introduced by the UN's International Maritime Organisation (IMO) to increase the safety of ships and the environment, and to improve traffic monitoring and

maritime traffic services. Ships larger than 300 tonn are required to have an AIS transponder on board. The exchange of data happens via VHF radio communication between nearby ships, AIS base stations, and satellites. Aggregated AIS data, i.e. down sampled to 1 message per 5-6 minutes are commercially available. The figure below to the left shows a

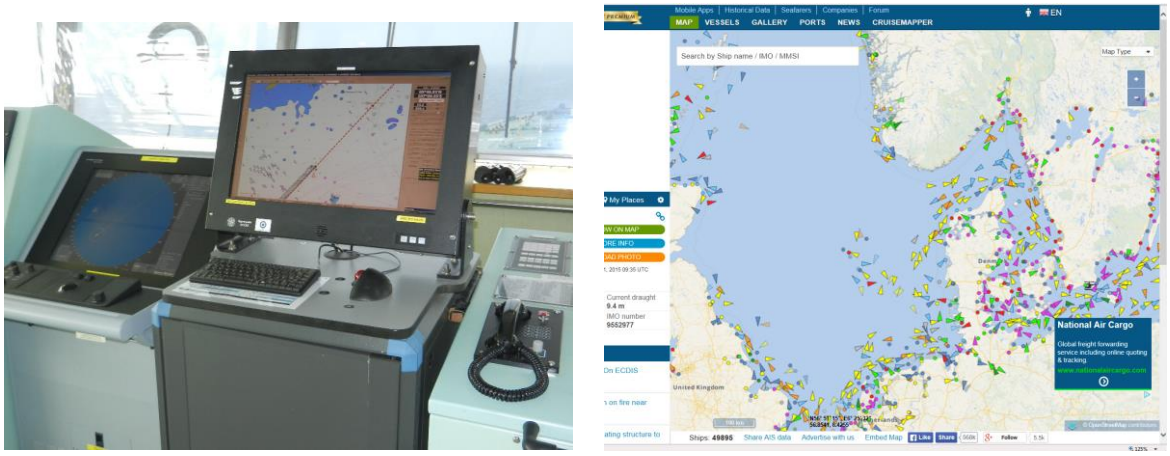


Figure 6: (Left) ECDIS work station on a bridge uses AIS to detect and identify other nearby vessels. (Right) Down sampled AIS data are increasingly available commercially to the public, here VesselFinder[182]. This use was originally not intended

b. Emission data for compliance reporting:

Most of emission information are collected, aggregated and reported manually. The raw data are either readings from meters, e.g. fuel consumption, ballast water, or are based on simple computations, e.g. sulphur emission based on fuel consumption and fuel grade. Manual tasks are error prone and therefore some ship owners are installing automated emission monitoring systems. Emission information is sent regularly (usually daily) to local authorities at shore or to HQ. Although emission raw data may constitute a large amount of data, the reported emission information is very limited, i.e. a couple of numbers per day, and do therefore not constitute a Big Data problem. Authorities on shore collect these emission data and aggregate it on a national level for trending of, input to or as verification of pollution reduction measures.

Figure 7: Example of ship emission

[182] http://www.vesselfinder.com/

c. Operational data for ship performance monitoring:
Operational data of a ship are available (i.e. communicated to shore) in form of a noon report which is a data sheet prepared by the ship's chief engineer on a daily basis. The report provides the vessel's position and other relevant standardised data to assess the performance of the ship based on its speed and environmental forces including weather conditions. Noon reports are also used by ship managers to assess the difference in the performance of the vessels or between two similar types of ships (sister ships) to outline solutions for underperformance or possible issues. The noon report is one of the important documents on board ships that is recorded and used for future references.

The chief engineer is responsible for preparing and sending the noon report to the company and shore management at a fixed time (normally during noon)[183]. The noon report is used to analyse the following parameters and performance: daily consumption of fuel and lube on daily basis, total cargo weight, distance covered from last port, distance to next port call, passage time, time in port, fuel/ lube oil to be ordered, fresh water to be ordered, calculate the Energy Efficiency Operation Indicator.

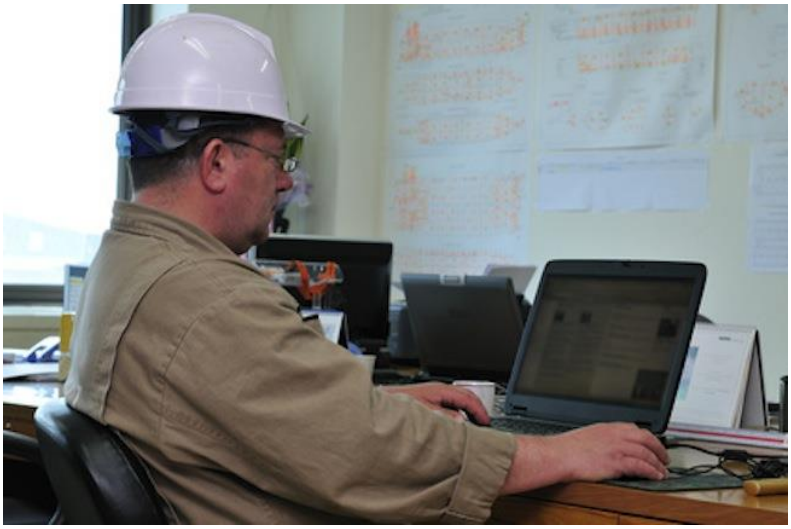


Figure 8: Operational data are collected and reported in a so-called noon report

d. Operational data for control of on-board sub-systems:
Modern machinery control systems incorporate an enormous amount of measurement instrumentation, including temperature sensors, pressure sensors, flow sensors, vibration sensors, current sensors, and the list goes on and on. They come in the form of mechanical gauges, electrical meters, transducers, thermocouples, resistance temperature detectors, etc. All of these devices provide valuable information to operators and are also essential for controlling equipment operation, providing alarms, or triggering equipment safety features, such as automatic shutdowns[184].

Most if not all of these sensor data are not accessible to others than the control system. Although some of the data is/may be useful for other purposes (e.g. noon reporting) they must in general be collected manually as many sub-system providers refuse to give access to their data stream for a number of reasons: either due to security concerns, or to hinder re-engineering, or simply to protect the data and/or applied methodology.

[183] http://www.marineinsight.com/marine/marine-news/headline/what-is-noon-report-on-ships/
[184] http://macsea.com/wp-content/uploads/Sensor-Reliability-Whitepaper.pdf

Figure 9: (left) Typical engine room console. All the raw data from sub-systems are processed, modified and aggregated on a level that is human understandable. (Right) Modern ships have installed thousands of sensors especially related to engine or other machinery control

e. Ship design data for structural and compliance verification:

Ship design data is a general term for information about the shape, hull, its blocks, sections, all structural elements, and materials used regarding a ship. Unless otherwise specified, it does not cover any piping, engine, electricity or any other aspects – just structure.

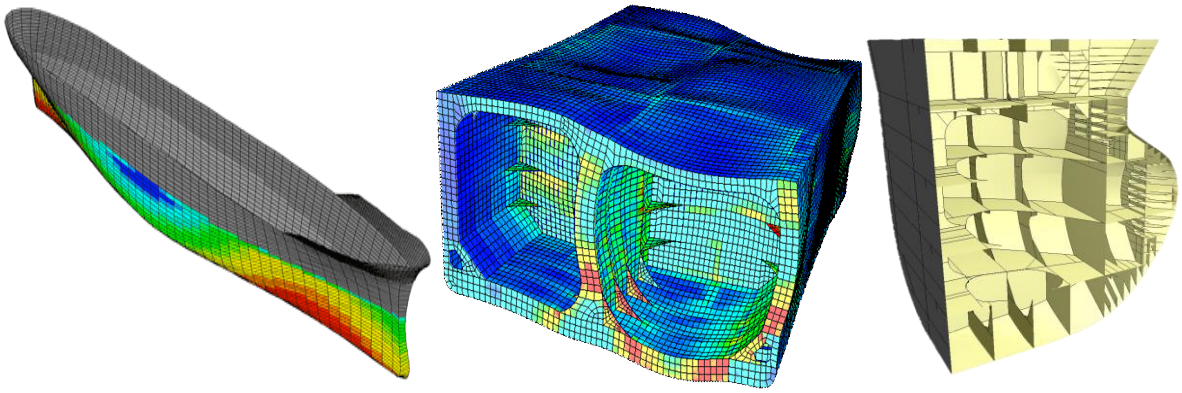


Figure 10:Examples of ship design data. (Left) Hull shape data for drag calculations, (middle) mid-section data for verification of buckling strength, (right) bow section data for strength assessment and weight calculations

Ship design data are usually in a proprietary format, again mostly due to business reasons. The main purpose of these data is to verify them against compliance to existing rules and regulations (as stated by the Class societies, IMO, natl. authorities). Ship yards and ship owners often regard these data as confidential as a new ship design may provide a business advantage to the ship owner (or yard). The amount of data is rather low - in the range of MB.

2.3 DATA FLOWS

Generally, the data flows between actors in the maritime industry are aggregated. The raw data feeds are contained within the subsystems supplier or the administrator of the data feeds such as National Costal Administration. The figure below shall visualize the data flows between the various actors in the maritime industry. The thickness of the arrows shall give a qualitative indication of the amount of data involved. The grey lines indicate emerging data flows.

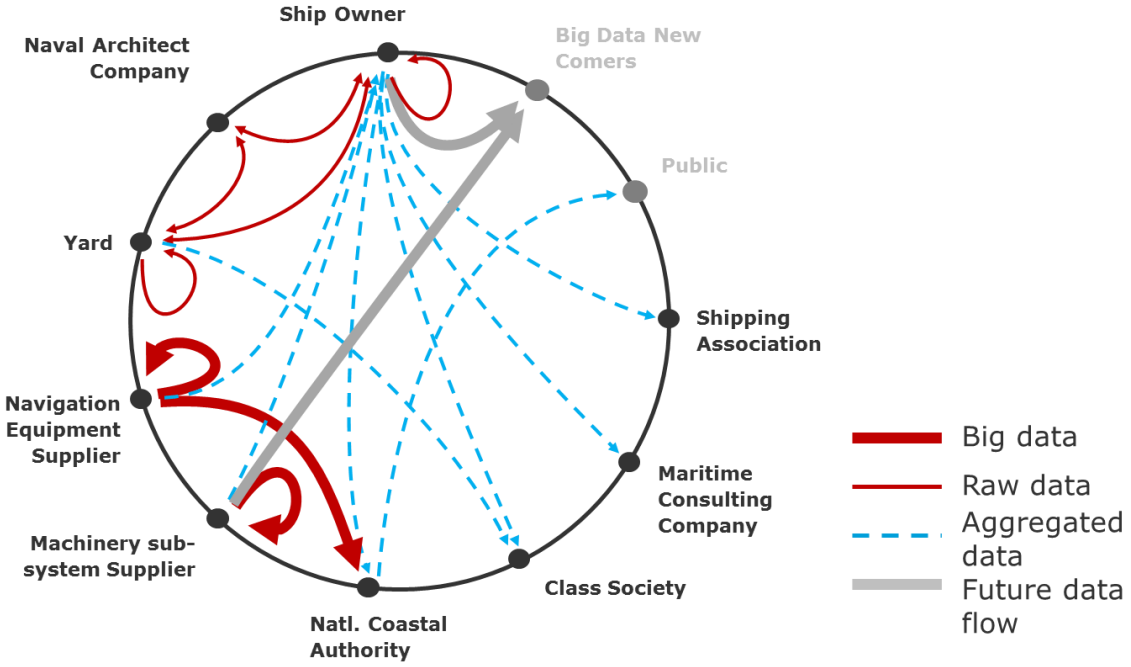


Figure 11: Overview of data sources and flows between the various actors in the maritime industry. The thickness of the arrows shall give a qualitative indication of the amount of data, thin arrows = KB (per day), thick arrows = GB/day. The grey lines indicate highly likely new data flows

A common denominator is the unwillingness to share any raw data, and in most cases we have observed that data is fist aggregated and then shared.

2.4 MAIN TECHNICAL CHALLENGES

Through the interviews, we have identified the following technical challenges in maritime industry. They can be categorised in the following four main groups:

1. **Acquisition**: most on-board (sub-) systems (e.g., electrical or machinery control systems) are designed as SCADA systems. Traditional SCADA systems are not designed to offer sensor network capabilities and do not to support Big Data technologies out of the box. These data streams are not intended for immediate human consumption but for machine-machine communication. Even manufacturers may not easily have access to the raw data. For any 'big data' application a data hosting interface will have to be set up.
2. **Curation**: monitoring system calibration. This is a central aspect in all data acquisition as a non- calibrated or a drifting sensor will provide wrong or low quality

data. Especially manual data input faces challenges of low data quality which is a main driver towards automated data acquisition. ALL interviewees cited data quality (either for raw or for aggregated data) as one of their main challenges.

3. **Storage**: limited storage infrastructure distributed and central. The interviews indicate that storage seems not be a too limiting factor as raw data are usually not stored (only aggregated data). However, for raw AIS data, storage requirement and handling falls into the category of big data. With increased coastal coverage of AIS receiving stations, the amount of historic AIS data will quickly grow into TB ranges. Even for down sampled AIS data storage requirement will increase considerably as well as the need for adequate data handling and analysis tools.
4. **Others**:
    a. **System access in real time**: Disconnected systems or limited bandwidth between the data acquisition and analysis/use. Many ships will not be within the reach of coastal communication networks for an extended period of time. Any application requiring real time access will have to use expensive satellite networks having limited bandwidth. This is especially true for AIS signals and for machinery control (sub) systems. The other by us listed data have not require real time requirements, neither do they have large amounts of data to transfer.
    b. **Security and privacy** issues related to increase system monitoring. Security was mentioned by ship owners and system providers (navigation and machinery) as fear that with increased connectedness somebody may hack into their systems. Privacy issues, and especially IP theft / industrial espionage and increased competition were mentioned by all interviewees. All players consider their data as business critical and consequently most were against making them freely available or share with others.

It must be pointed out that the main challenges for adoption of Big Data technologies not technical but rather related to human, organisational and financial issues, for example:

- The by far largest hurdle in adopting (big) data driven solution is the short investment time horizon of a couple of months. In shipping the dominating doctrines are: “don’t fix what ain’t broken”, “only if it is required by law”. This was also clearly reflected in the interviews. As any investments in Big Data technologies often leads to large costs, not only direct cost for technology purchase, but indirect costs related to training, reorganisations, temporary reduced efficiency, cannibalism of existing solutions, etc. The primary focus of this industry is on earning money through profitable transport deals and less on cutting costs.
- Many ship owners do no longer directly employ their own ship crew, but they use crewing agencies. Consequently, this leads to frequent crew shifting, which often is not familiar with the particular data gathering and reporting schema for that vessel. Additionally, the training costs increase drastically and results in low data quality due to non-familiar routines and processes.
- There are often tight bulkheads between the different organisational units, which prohibit the establishment of routines or incentives to deliver high quality data. For example, even stable crews often deliver low data quality as they do not know what the data are used for and do not see their importance.
- Any form of manual data gathering is extremely prone to low data quality. Some of this data collection could be automated and thereby provide high quality data but this requires investment in an automated system. Investments, especially in the maritime industry, require a rate of return on a short time horizon in range of months. Short-

term profitability computations effectively stop most deployment of automated data collection systems.

2.5 BIG DATA ASSESSMENT

The case study strongly indicate that the maritime transport sector is in general at a very early stage when it comes to using data driven services, or any form of "Big Data" utilisation. The case study strongly indicates that major parts of the maritime transport sector are in a very early stage for adoption of "Big Data" solutions. The ship owner may represent one extreme where "Big Data" is mainly business data and mandatory environmental reporting data collected on a day basis, consisting of just a handful of numbers. There is no uniform conception or definition of what is meant with "Big Data". Figure 2 illustrates qualitatively the maturity of the maritime industry with respect to (big) data and the need for (big) data driven solution. It may also be pointed out that there is a wide range within a sector, e.g. yard, showing large variations in maturity.

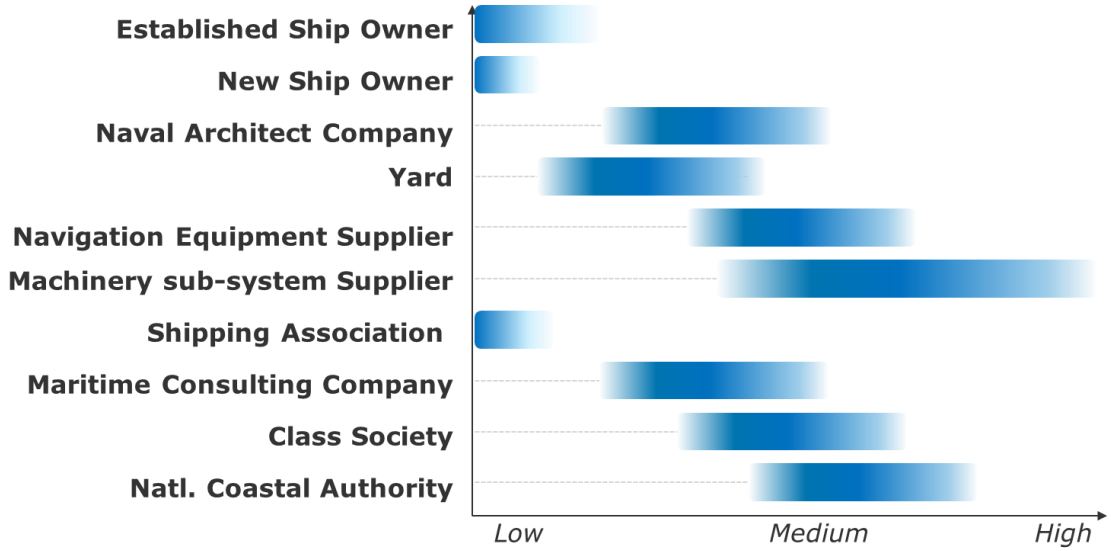


Figure 12: Maturity and need for Big Data solutions in the maritime industry

3 ANALYSIS OF SOCIETAL EXTERNALITIES

In the BYTE D3.1 Case study methodology report, it was suggested to address barriers and enablers to the use of "Big Data" as there exists an obvious relationship between externalities of an activity and consequential reactions from affected third parties.

3.1 IDENTIFICATION OF EXTERNALITIES WITH HELP OF BARRIERS AND ENABLERS FOR DATA DRIVEN SOLUTIONS

In Table 45 and 5, we present barriers and enablers that were identified for adopting data driven solutions in the Maritime industry. The process of identifying societal externalities is based on the following assumption: *if an activity causes a negative externality then the affected party would oppose that activity, hence appear as a barrier, respectively with positive externalities and enablers.*

Table 45: Barriers for adopting data driven solutions in the Maritime industry

	Barriers	**Exter-nality**	**ID** (Table 43)
1	Growth in data volume		9
2	Limited connectivity and bandwidth / infrastructure, real time requirements		6
3	Existing tools no longer adequate for data storage	+/-	9
4	Existing SW tools no longer adequate for analysis of data (in reasonable amount of time)	+/-	9
5	Existing mathematical analysis methods may not utilize the full potential of big data	+/-	7,8
6	Increased complexity system and comprehensibility		6
7	Total removal of human element, i.e. no last sanity check	-	5
8	Data aggregation: high volume => small data/aggregation and end user customization		5,8
9	Avoid over optimization	-	7
10	Assurance of confidentiality of data, Protection of IP (re-engineering)	-	3,9
11	Reluctance of sharing data		1,…6,7,8
12	Ownership of data not resolved (who owns the data, e.g. ship owner or (sub-) system provider?)	-	3
13	Increased dependency/reliability on software		9
14	Increased dependency/reliability on sub-contractors/subsystem suppliers		8
15	Development driven by system supplier, NOT user => little collaboration due to competition		8
16	Little trust in actors and data, analysis of data due to different agendas and complexity		8
17	Data repository for sensitive data missing		2
18	Data quality of (semi) manually collected data		5
19	New actors challenge existing business models and role of organization		9
20	No clear idea what to use the data for		1
21	Need a holistic view on the data and processes around		9
22	Lack of "big data" strategy in company,		8
23	Division of industry in big data achievers and losers (e.g. too small company)	-	6
24	Reluctance to necessary re-organisation, increased frequency of re-organisations, tech. upgrade		3
25	Reluctance to increased personal monitoring		8
26	Increased coordination between actors	+	3

27	Integration of existing with future tools/systems (legacy systems become barriers, silos)		1,3,7,8
28	Big data conceived as 'black box' technology		8
29	Difficult access to (big data) expertise	+/-	5,7
30	Loss of internal knowledge due to necessary outsourcing		9
31	Increased need for training	-	2,3,5
32	Legal void, need for increased authority involvement, need definitions, guidelines	-	3
33	Owner cannot provide legal requirements on documentation as system provider refuses to disclose IPs/confidential info.	-	8
34	Too slow adoption/adjustment/blocking of existing rules and legislation in some aspects		8
35	Too fast / frequent changes with respect to other aspects		4
36	Proprietary formats		8
37	Return on investment / profitability difficult to document/too long time horizon needed		1,2
38	Well established industry processes and collaborations, which are difficult to change/disturb	-	10

Table 46: Enablers for adopting data driven solutions in the Maritime industry

	Enablers	**Ext**	**ID**
1	Better and more accurate asset management and evaluation		5,7
2	Deeper and more reliable understanding of involved risks and opportunities		5,7
3	Better optimization of business & technical processes and design, i.e. less resource use	+	3,5,6
4	Better benchmarking of system or sub-system provider	+	3,8
5	Capitalising on synergy effects		3
6	Better and more end user involvement	+	8
7	Faster and better access to data		6
8	Can change charter market to be more environmental conscious		6
9	New service offerings /business opportunities	+	2,4
10	Unintended/not designed monitoring opportunities of other aspects, can use same monitoring system/data to extract other info	+/-	5
11	Multi-objective optimization		2
12	Learning from others		1

3.2 SOCIETAL EXTERNALITIES

According to OECD[185], "externalities" refer to situations when the effect of production or consumption of goods and/or services imposes costs or benefits on others, which are not reflected in the prices charged for the goods and services being provided. Observe that externalities are related to processes, i.e., production, service, or use, and not to the product itself. That is, it is NOT the "Big Data" platform per se that causes externalities, but there are always the processes that can lead to externalities. In addition, it may not necessarily be that the existing processes may evoke a reaction, i.e., cause an externality, but the opportunity/risk given by the existence of the connected data. As externalities are reciprocal, one may find a positive externality for any negative, and vice versa. In Table 47, we present the identified externalities based on the information about barrier and enabler presented in Table 45 and Table 46, obtained during the conducted interviews.

Externalities are closely tied with processes, i.e. the usage of (big) data, they may be revealed only when analysing these processes. Realize that originally there may be no unintended side effects associated with a given data process. However, externalities can emerge when these

[185] http://stats.oecd.org/glossary/detail.asp?ID=3215

data are used for a purpose not intended / thought of in the beginning. That is, trying to identify all externalities in connection with a given data source, is equal to identifying ALL potential usages of these data that may emerge in the future – which is totally impossible.
Posing the interviewees with the question about what externalities are/will most probably arise from the future use of their data, they could not name any externalities. The only raised issue was "privacy" concerns. However that almost all privacy concerns are about potential future misuse of data – NOT current misuse!

The big maritime data focus group did not result in many new aspects related to externalities caused by the use of (big) data in the maritime industry. However, Lars Arne Skår provided the example of an unintended side effect of shipping contracts from: "Using Big Data to change trade in sea based container transport". Here, pricing data contained in container shipping contracts were collected and a benchmarked against each other to get an indication of how cheap/expensive a particular shipment was. Although the source of this example is a start-up company, this container pricing benchmarking service has already had a significant impact on the container shipping market as the service makes suddenly the pricing structure transparent and globally available. Therefore, large price fluctuation has been smoothed out. This might be considered as a positive externality for those who want to ship containers, but negative externalities for all the shipping companies who earned god money on offering higher prices.

Please note that the externalities presented in Table 47, could not map into the initially defined taxonomy of externalities. Due to the vague (i.e., hard to quantify) nature of the externalities we could not create a clear mapping between Maritime industry specific externalities and the project-wide predefined externalities. It is beyond the scope of this report to provide a direct taxonomy between the enablers/barriers and positive/negative externalities. Often each of the identified externalities could refer to several of the original taxonomy, and to avoid ambiguity we chose not to mention possible candidates.

Table 47: Identified Externalities in the maritime industry. The ID column codes for the interviewees (see Table 42 or Table 43). Some of the externalities were identified by the authors when aggregating the results, these instances are coded by ID = 0.

Barrier & Enabler ID	ID	Type	Externality	Code
B23,32 E9,10	2,4,5	 + + -	As data may be used for something else (as originally intended), a (sub) system provider/ data collector may: • involuntarily be assigned a new responsibility. • exploit new opportunities, • missuses the data	
B23,29,32 E9,10	5,6,7	+	Little expertise/high dependence on data (driven solutions) may open new business opportunities for others.	
B32, E10	3,5	-	Banks/Insurance/financing institutions may require/demand access to data streams	
B3,4,5,38 E3,4	3,5,6,7,8,9	+	More data & better models may result in process/product optimization and therefore using less non-renewable resources (e.g. fuel, metal etc.)	
B7,9	0,5,7	-	More data & better models may result in a more optimized solution for a specific problem, but if problem changes the solution may be worse suited than before. That is, effectively reducing existing safety margins (i.e. less resilience).	
B26,29,32	3,5,7	-	More advanced use of data may require that current competence of authorities and regulating authorities are not sufficient	PC-ETH-3

B10,23,26,33,38 E4	1,2,38	+	Common benchmarking may enable equal level playing field	
B3,4,5,24,29,31	1,2,3,5,8	+	Increased use of data (driven services) will require changes in training/education	PC-BM-2
B32,33,34	3,4	-	Combination of data (sources/results) will require frequent changes in the legal framework	PO-LEG-2
	4	+	Because of modernisation/upgrade of data transfer capacity/capability, other actors may piggyback this development with their services.	
B6,11,13,14,16,28,29 E2	8,9	+	Data quality and trustworthy data /analysis results may require 3rd party trust services.	
B12,10,33 E12	3,5,7,8,9	-	Automated collection of data will result in increased opportunities for industrial espionage	
B6,7,13, 16,28,30	5,6,8,9	-	Increased system complexity/SW dependency/advanced analysis will make the process from data generation to decision taking less transparent.	
B24,32,38	3,8	-	Services based on (combination of) data stream and mesh-ups will require an adaption of existing security practices and legal requirements	PP-LEG-2
B7 E1,2,3	0,5	+/-	"Big data" may remove human fail-safe role through fully automated processes. It may also lead to data generated models as basis for decision taking rather than human-modelled decision processes.	
B10,11,22,26	1,..,9	-	Access to data is hampered due to a "my data are unique and most precious" attitude. The reason seems to be a lacking/non-up-to-date legal framework protecting the data and to a larger extent the lack of a profit sharing business model where data providers will get revenue share.	
B21,23,24,29,28,27,30,35,37,	1,2	-	Many small players may experience increased business pressure from larger ones as they cannot afford to introduce expensive data driven solutions (endangering small businesses)	OO-BM-5
B27,37	1,2,3,7,8	-	Short term financial appropriation rules / demand for high RoI effectively stops most investments in data driven solutions. RoI time horizon in shipping industry usually 3 months!	OO-BM-6
B32,34 E4	3,8	+/-	Authorities are considered central in fostering data driven solutions through new regulations and financial incentives, legislation (IP), standardisation, benchmarking.	

We point out, that this task is very subjective as someone with another background or understanding of the maritime industry may conclude differently. That is, people with a different background will most probably pose the questions differently and interpret the answers from the interviewees differently. As stated above, additional externalities may emerge as other future usage of the data is envisioned.

It was the main task of the authors to contemplate potential future externalities based on the collected answers from the interviewees. A potential externality (potential because the process using some data may be hypothetical/not yet existing) may therefore not necessarily be assignable to a specific interview. Externalities identified by the authors are coded by ID = 0 in Table 47.

4 CONCLUSION

Shipping is concerned with the transport of more than 90% of global trade. The maritime industry goes usually unnoticed, due to factors like low visibility, less planning, uncertainty, and long tradition. Further, much of the industry is characterized by small financial margins, small organizations, high fragmentation and consolidation. Their processes are lean and most process changes occur only due to regulatory changes.

The central aim of this case study was to identify externalities associated with data sources in maritime transport industry. A fundamental challenge in identifying externalities lies in the fact that data can be used for a purpose not intended / thought of in the beginning which could give rise to externalities. That is, trying to identify all externalities in connection with a given data source, is equal to identifying all potential usages of these data that may emerge in the future – which is totally impossible. In our case study, we therefore have focused on the originally intended use of data by interviewing representatives from industry actors with different roles. The maritime transport sector is characterised by a very wide span in their competence, capabilities and utilisation of data. The case study strongly indicates that major parts of the maritime transport sector are in a very early stage for adoption of "Big Data" solutions. The ship owner may represent one extreme where "Big Data" is mainly business data and mandatory environmental reporting data collected on a day basis, consisting of just a handful of numbers. At the other extreme, we find the represented of the equipment supplier who use advanced sensor technology to monitor their equipment only. The amount of data can reach GB/day for a monitored system. In other words, there is no uniform conception or understanding of what is meant with “Big Data”. A common denominator is the unwillingness to share any raw data, and if they have to, this is only done on an aggregated level. Competition is the main reason for that.

The interviews indicate that in long term, this sector will adopt solutions that are already developed in other industries such as land logistics and offshore Oil & Gas. Indications were also gathered that there is a high probability that new actors will enter the maritime industry because of the onset of ‘Big Data’ (data driven solutions/services).

The interviews indicate that in the long term, this sector will be approached/invaded by new players with extensive IT and data competence such as IBM, Google, Microsoft, and a myriad of small IT companies. As many of these companies also provide service in other industries, the attitude towards externalities in shipping may change. Our analysis shows that the identified externalities are ambiguous and are not restricted to maritime industry. It seems that externalities caused by data utilisation are very low or non-existing. In addition, the shipping sector does not regard externalities as important as any effect of externalities on e.g. legislation, safety, cost reduction etc. is far beyond their budgeting and investment time horizon (usually a couple of months). Further, as long as there are not legal requirements in place that will force the maritime industry to change any of their processes they will not change as any change is considered as a cost.

The case studies also strongly indicate that this sector is characterised by a very slow adoption of new data driven solutions. In general, ship owner are not the first to adopter new technologies, they are extremely conservative and do not see immediate business advantage given by data driven services. There is evidence that the main reason lies in the fact that the primary focus of this industry is on earning money (i.e., not surprisingly), this is done through profitable transport deals and less on cutting costs. Introduction of new technologies is largely about doing things faster, better, cheaper, which is mainly about cutting cost and

will therefore get secondary priority. In other words, there is great resistance in voluntarily adopting new technology. The interviews clearly point to the important role played by authorities, as some stakeholders within the maritime industry will not react unless required to do so by legislation. Relevantly, the authorities' sole focus is on technologies increasing safety and environmental protection, such as oil spills, accidents or emissions.

SMART CITY CASE STUDY REPORT – *BIG DATA IN A DIGITALIZING CITY: THE PROMISE, THE PERIL, AND THE VALUE*

SUMMARY OF THE CASE STUDY

The smart city case study focused on the macro-view of the creation of value from potentially massive amounts of urban data that emerges through the digitalized interaction of a city's users, i.e. of citizens and businesses, with the urban infrastructure of resources such as energy and transportation, social and administrative services, etc. We have created a focus group representing the main stakeholders from the city, representatives of the energy as well as mobility industries of a city, multinational technology solution providers and smart city consultants who are thought leaders and invited speakers at big data related smart city events. In addition, we followed up on the insights of the workshop through interviews with further senior experts from smart cities and big data analytics experts.

The resulting material is presented in the following for further analyses through the EU BYTE working groups for cross-analysis and application of foresighting methods to compile the necessary recommendations for the European policy and research roadmaps. The first part of the case study creates a general overview on the current state of big data in smart cities by examining data sources, data uses and flows, by discussing the main technological challenges. The state of big data utilisation in digitalizing cities can be summarized as developing. Some cities are currently building the necessary big data structures, be it platforms or new organizational responsibilities.

The second part lists and analyses the identified positive and negative societal externalities divided into economical, social and ethical, legal, and political externalities. The economies of digital, especially big data, favour monopolistic structures, which may pose a threat to the many SMEs in cities and the small and medium cities. However, open source and open platforms, open data, and even open algorithms crystallize as a short cut and "technology-driven form of liberalization" accompanying the big data movement in cities, which has the potential to level the playing field and even spur more creativity and innovation. The potential of big data to be used for social good is immense especially in the digitalizing city. However, there is a range of pitfalls, we, as a society, need to take care of: The strong reliance on data-driven services will need a new debate on how we can assure "enough" equality, when there are so many different reasons why not all citizens will reap value from data in equal amounts. We conclude that socially desirable outcomes must be formulated first. Personalized, i.e. citizen-centric, policy-making and services with immediate feedback become possible for the first time. Policy makers should take advantage of digitalization and use the positive potential of big data for policymaking for the European cities.

1 OVERVIEW

The number of smart cities worldwide will quadruple between 2013 and 2025 according to a report from IHS Technology[186]. In this report smart cities are described as the integration of information, communications and technology (ICT) solutions across three or more different functional areas of a city mobile and transport, energy and sustainability, physical infrastructure, governance, and safety and security[187]. Both research and development of ICT

[186] https://technology.ihs.com/507030/smart-cities-to-rise-fourfold-in-number-from-2013-to-2025
[187] http://press.ihs.com/press-release/design-supply-chain-media/smart-cities-rise-fourfold-number-2013-2025

for urban data can work from a united perspective in the deployment of useful big data applications in the smart cities sector.

1.1 STAKEHOLDERS, INTERVIEWEES AND OTHER INFORMATION SOURCES

For this case study, the city and technology providers (multinationals, start-ups, and non-profit organizations) were the main stakeholders under study as detailed in Table 48. At the time of this writing citizen or consumer advice representatives are not yet visible in the new discourse about big data in a digitalizing city.

Table 48 Main stakeholder organizations in the smart city case study

Organization	Industry sector	Technology adoption stage	Position on data value chain	Impact of IT in industry
European City	Public Sector	Early majority	Acquisition Analysis Curation Storage Usage	Strategic mode
Technology Provider	Start-up, Energy	Early adopter	Acquisition Analysis Storage Usage	Turnaround mode
Technology Provider	Non-profit, Mobility	Early majority	Acquisition Analysis Storage Usage	Turnaround mode
Technology Provider & Research	Multinational, Smart City	Early majority	Acquisition Analysis Storage Usage	Strategic mode

In order to conduct the case study analysis, we created a focus group representing the main stakeholders from the city energy as well as mobility industries of a city, multinational technology solution providers and smart city consultants who are thought leaders and invited speakers at big data related smart city events. The agenda and the main outcomes of the focus group are included in Appendix D.

Table 49 codifies and summarizes the sources of focus group insights that we will be citing and referencing throughout this document for further analyses through BYTE working groups. FG refers to the insights from the group discussions consisting of 2 smart city experts, 1 mobility & 1 energy services experts from the studied organizations, 2 smart cities experts from consulting firms in smart city and clean tech cluster. FG-City refers to the insights from the break-out session group made up of a mixed group of city representative, smart city consultants, and researchers. FG TechPro refers to the insights from the break-out session group made up of a mixed group of technology provider, smart city consultants, and researchers. FG-Citizen refers to the insights of a mixed group of researchers who described themselves “regular,” “techno-capable,” and “involved” citizen, with which we aimed to capture some insights reflecting the most important stakeholder of the city, the citizen. However, it must be emphasized that the citizen as stakeholders need to be more involved into the discourse of creating value from big data, which mainly is user data. Throughout the citations, analysis, and main conclusions, this common theme stands out.

Table 49 Constellation and codes of the focus group insight sources

Code	Source	Event	Description
FG	2 smart city experts, 1 mobility & 1 energy services experts from the studied organizations, 2 smart cities experts from consulting firms in smart city and clean tech cluster	BYTE smart city focus group workshop	Focus group on big data in a digitalizing city, stakeholder mapping and consolidate discussions after break-out session
FG-City	Mixed group of city representative, smart city consultants, and researchers	BYTE smart city focus group workshop	Break-out session discussion
FG-TechPro	Mixed group of technology provider, smart city consultants, and researchers	BYTE smart city focus group workshop	Break-out session discussion
FG-Citizen	Mixed group of researchers who described themselves techno-capable and involved citizen	BYTE smart city focus group workshop	Break-out session discussion

The interviews complemented the focus group, and enabled us to clear follow-up questions or collect alternative and/or more detailed perspectives. The interviewees were selected based on their field of work or study and their seniority. Table 50 codifies the interviewees according to the EU BYTE case study methodology in order to enable cross-analysis across sectors. The codes will be used throughout this document to reference insights from the interviewees.

Table 50 Selected interview partners and codes for the smart city case study

Code	Organization	Designation	Knowledge	Position	Interest
I-MC-1	Manchester City Council	Senior Technical Manager	Very high	Supporter	Very high
I-AI-1	German Centre for Artificial Intelligence	Senior Academic	Very high	Supporter	Very high
I-CG-1	City of Ghent	Senior Business Manager	Very high	Moderate supporter	Very high
I-SM-1	Rotterdam School of Management	Senior Academic	High	Moderate supporter	High

1.2 ILLUSTRATIVE USER STORIES

Digitalized "Physical" Infrastructure

Energy, Mobility, and Information networks make up the digitalizing physical infrastructure of smarter cities. City nodes, e.g. private or commercial buildings, train stations, etc. Some nodes are hubs such as central train station, airport, or industrial parks, etc. are connected by infrastructure for transportation, energy, and information. Each infrastructure can be seen as a multimodal resource flow network, with different modes of transportation: roads, railways lines, or forms of energy: gas, heat, and electricity. Situational awareness on the city and

cross-optimization of these resource networks is a secondary trend, which is allowed by the convergence of technological advancements and platforms. Each entity or mode in these infrastructures can be seen as a big data application in itself: a solution that not only makes use of big data and but also adds to the body of data.

> A typical smart city project is being rolled-out here regarding city lighting. Current light bulbs shall be replaced by LED, with the **major goal being modernization and carbon reduction through efficiency increase**. For the first time computer control will be possible to switch on/off or dim the lights, at different locations. In the old system, only data about the location of the light bulbs was being managed. With the digitalization of this [lighting] infrastructure the city will also manage connectivity to control centre, which needs to be robust enough to collect real-time data every few minutes and faster. **Most of the new data will be about control** – and it will be bigger, i.e. streaming sensor and control data. If we wish this data can be put into a pool of energy data, when analysed, the city can look at energy usage patterns; correlate yet with other data sources etc. For the current lighting system, however, the city only has location data about the lighting poles. So, most of the new scenarios will be about controllability and control, which then will **require analysis of real-time usage/operations data.** [I-MC-1]

Participatory Sensing[188]

Smart Santander project[189], a public-private partnership, is placing sensors around various European cities in order to gather data, as well as take advantage of what citizens are willing to contribute through their smartphones and specialized software. It takes advantage of the ability of these devices to be connected to people as well as to the core network. Data analytics, IoT, and some aspects of social media are blended so that problems are found in real time and conveyed back those who can fix them.

> Another use that **motivates the sensorisation** of a city is the quantifiability of improvement projects. Such new **improvement project** is the pedestrianization, i.e. areas where only bikes, busses and taxis are allowed, which means less traffic for that area – but the actual amount of traffic mostly remains the same and must be redirected. Sensors installed prior to such a project on the roads can measure current state. Assumptions and simulations can be made based on the real data to run numbers on possible outcomes. But most importantly, the data after the improvement project can be compared, analysed and used for future improvements. **The city becomes quantifiable**. [...] There are a lot of planned investments in the pipeline, such as the pedestrianization example, and the aim is to quantify the improvement through sensorisation from the beginning. Such **evidence-based decision making** is a sound business case for cities. [I-MC-1]

Linked City

Dubl:nked[190] is an innovative new data-sharing network. The network is seeking to link data, sectors, skills and people to generate new commercial opportunities for the Dublin Region. Dubl:nked will also provide the Dublin Region's first Open Data Platform which makes public data available for research and reuse. The city is explicitly utilizing data as a resource to invite new data-driven economy actors.[191]

[188] http://www.ubmfuturecities.com/author.asp?section_id=459&doc_id=526800
[189] http://www.smartsantander.eu/
[190] http://www.dublinked.ie/
[191] http://www.dublinked.com/?q=aboutus

Public Safety

Open data and cloud-based big data analytics can be used to improve the efficiency of police and fire services by capturing and correlating the analysis of all data coming from various systems installed in the city, including surveillance cameras, emergency vehicle GPS tracking, and fire and smoke sensors[192]. Predictive policing uses historical crime data to automatically discover trends and patterns in the data. Such patterns help in gaining insights into crime related problems a city is facing and allow a more effective and efficient deployment of mobile forces[193] and significant decrease in crime.

2 DATA SOURCES, USES, FLOWS AND CHALLENGES

2.1 DATA SOURCES

In order to gain a macro view of the relevant *big data sources*, we consulted the focus group in the workshop. The focus group consisted of stakeholders from the "city," "mobility" industry, "energy" industry, city "technology solution providers", as well as EU BYTE researchers, who considered themselves "techno-capable citizen" or "involved citizen". The resulting map of digital city stakeholders and their most interesting data is depicted in Figure 13.

In the analysis of the stated big data sources we concentrated on what type of data or data source is relevant for more than one stakeholder. This question is interesting since it should indicate the data sharing motivation and may shed some light into how to kick-start data ecosystems and the state of data flows, as briefly touched upon in section 2.3. Same data sources from different stakeholders are highlighted in Figure 13:

> The city and general population are very much concerned about their mobility; hence, **mobility data** (violet) is at the core of the city. [FG]
>
> The involved citizen additionally cares about the resource conditions of the city, hence **environmental data** (green). [FG]
>
> **Energy data** (green) is at the core of the energy data start-up, whereas for smart city technology and consulting firms **EarthObvs-spatial, EarthObvs-referenced data** (orange) is equally of importance. [FG]
>
> Smart city technology and consulting firms are additionally focused on **operational and process data** from infrastructures (blue). [FG]

[192] http://www.accenture.com/us-en/blogs/technology-blog/archive/2015/02/11/iiot-and-big-data-analytics-help-smart-city-development.aspx
[193] http://www.predpol.com/

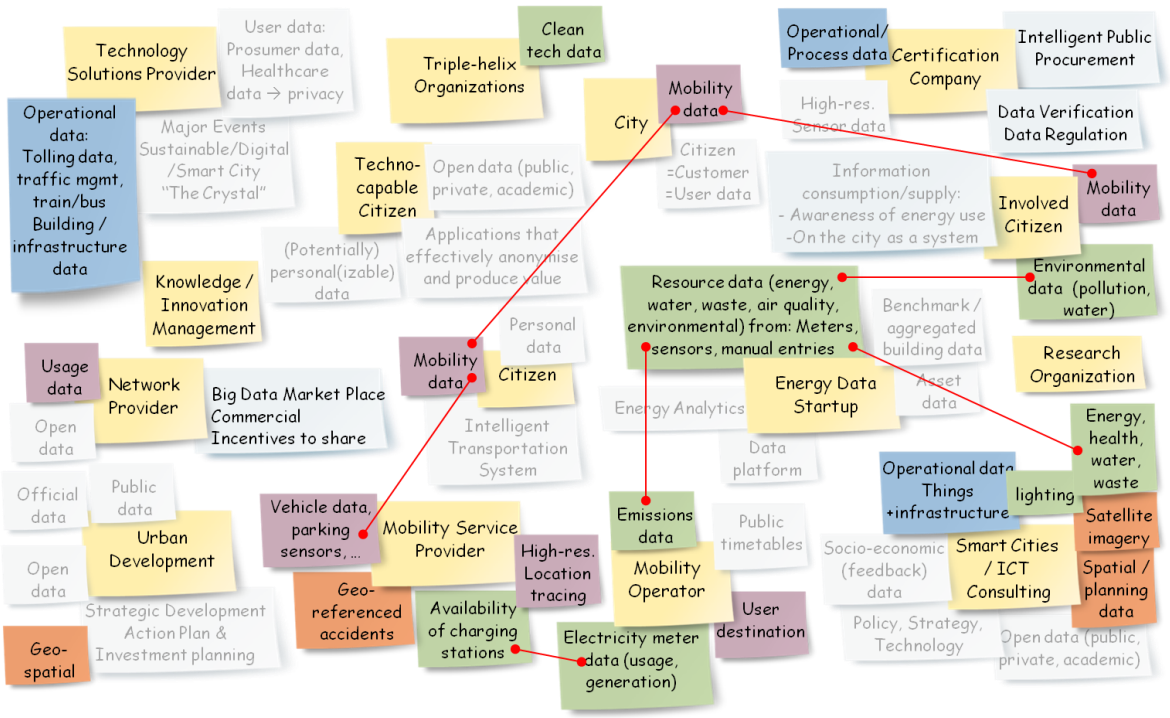


Figure 13 Digital City stakeholders, their relevant data sources and usage. Same or similar data types / sources are highlighted. Interesting data flows between stakeholders are drawn in red

Digitalization can be identified as main driver behind the creation of big data sources. Many data sources are associated with the modernization and digitalization of infrastructures or services within the city.

> A typical smart city project is being rolled-out here regarding city lighting. Current light bulbs shall be replaced by LED, with the major goal being **modernization and carbon reduction** through efficiency increase. [I-MC-1]

The digitalizing city encompasses a myriad of existing and potential data sources, since entire sectors such as energy, mobility as well as other businesses from health services, travel to infotainment are actively engaged in the city:

> The city [...] has three areas with **sensor stations**: the airport, city centre, and at the university. [I-MC-1]

> Cities and administrations do have a lot of **statistical data** on general public, e.g. obesity, healthy eating, detection rate on cancers etc. [I-MC-1]

However, many of the existing data sources are kept "small" due to technical, organizational, and historic reasons, which will be discussed in section 2.5:

> If you look closely at the data that is being managed by the city, it is *not really big data*: **planning data**, some **CRM management**, **local taxation** data, **transactional data** etc. Traditionally, like many other sectors cities have been managing *only the necessary data – not all data*. [I-MC-1]

New data that is being acquired from existing or new sources is more likely to be bigger, GPS-synchronized and coming from people living in the city as well as resources and

infrastructure utilized in the city. Data being correlated also generated new data in form of insights, error logs, etc.:

> In the commercial domain we have millions of transactions, whereas in the public realm we are more interested in **status data at specific times and locations**: e.g. **where** is the **bus** now? **When** will it be here? **Energy usage** data, such as **electricity, heating**, etc. as measured by sensors. [I-MC-1]
>
> [...] systems that generate **real-time data**: lighting, busses, energy district, and building information systems. The data is captured by real-time data generators, **smart devices** [...].[I-MC-1]
>
> [...] **mobile phone data** has a lot of **metadata** that can help in extracting **new insights**, especially **when correlated with other data**. However, it also requires peoples' permission and understanding of data. [I-MC-1]

2.2 DATA USES

Data uses in the smart city context can be categorized into high level purposes, which certainly can also be found in other domains, such as planning & reporting (of administrative processes as well as events or the city itself), understanding, improving & optimizing:

> **Reporting rules & regulations**, city **performance benchmarking**, **budget planning** are typical uses of data which create the **need for a 360° view** of the city. Centralized administrative data is already being used in some cities. [FG-City]
>
> Access to and analysis of massive amounts of natural language and sensor data enables to **automatically infer semantics**: Sensor data such as measurements on movement etc. from the same surroundings, i.e. in time and space, can be used as **context data, or as data-driven semantics**. At the same time these multiple data channels can be tapped into to have a **better understanding of natural language**.[I-AI-1]
>
> Data is also used in the course of **mega or micro events** within the city. [FG-City]
>
> This [statistical] data can help in **understanding behaviour**. Only then behaviour can be changed. For example, children from a district may eat less fruit, because there are no fruit shops nearby. Seeing this as evidenced by data can lead to directed, hence **faster and more effective, countermeasures**. [I-MC-1]
>
> Another use that motivates the sensorisation of a city is the **quantifiability** of improvement projects. [I-MC-1]
>
> Big data in a digital city can be used to (a) optimize the processes (b) improve the planning. [I-AI-1]
>
> When compared to other domains, smart city will be characterized by the ability to put **real-time data** to use **to determine best or optimal actions**. [I-MC-1]

Increasingly more versatile and newer data sources find their ways into existing processes. Sensors, many newly deployed, are stated as the main sources of big data in a digitalizing city, as stated in section 2.1. Metadata, as associated with mobile phone data, as well as natural language, the main type of data in social media, are increasingly being used in control centres of transportation or emergency control. The new type of data we are seeing is primarily the data of the user, citizen, who is either actively participating in the city processes through crowdsourcing initiatives, such as "citizen reporters," or just participating online and sharing information about their surrounding, the city:

> Modernizing city technology, sensor deployment etc. are needed and created new data will also be used in **city planning and design**, as well as in **city operations**. Examples of **crowdsourcing** have been tested in some cities for citizen bottom-up reporting, or citizen request data for reporting as a Twitter app. [FG-City]
>
> **Crowdsourcing** is also used by technology providers for co-ideation and tapping into **citizen-led innovation**. [FG-TechPro]
>
> **Mobility management** in general, but also ensuring **reliable emergency response** as well as enabling **resilience** based on real-time data are typical uses of data by the city. These data are used in **control centres**. Increasingly, anonymised and aggregated **mobile phone data**, and **social media** monitoring find their way into usage in these applications. [FG-City]

One differentiating area of the smart city case study can be circumscribed as "digitalizing utilities of care:"

> It is not long before we will see the creation of further **utilities of care** [groceries, mail, health services], as we are used to with gas, water, electricity etc. [I-AI-1]

However, even in this very specific case, the data use relates to a very common big data pattern: customer experience. Digitalization and creation of more utilities of care will result in better **citizen experience**:

> Regular commuters and the **need for getting from A to B on time** in general, motivate the use of **mobility data**, but also **combined use** of **travel itinerary**, **calendar**, and **meeting management data**. [FG-Citizen]
>
> Google Now or City Apps for **navigating** within the city require use of **mobility data**. [FG-Citizen]
>
> Shopping **needs move online** to Amazon.com and parcel station **near** home or work for **pickup items in the physical city**. [FG-Citizen]
>
> In home-town or in foreign city there is always the need to **find things, search for things**: events, hotels, babysitter etc. Web Search services, city apps, comparison web sites or tourism platforms such as Travelocity are used for this need. [FG-Citizen]
>
> Citizens require **access to public services** and health services in their city and region, or when in a foreign city. In these cases or for personal record keeping, **mobility or personal data** is of interest. [FG-Citizen]

Many of these above examples of better citizen experience through bundling and creation of more **utilities of care rely on real-time EarthObvs-spatial data**, i.e. when and where an item/person/event of interest is as **to avoid waiting**/queuing and better utilisation of one of the most valued resources we have: time.

2.3 DATA FLOWS

Similar to the discussion with data sources, in the smart city case study we need to resort to the more complex but enlightening macro view, because otherwise we are confined in scenarios of siloed sectorial perspectives, such as solely energy-related or solely mobility-related scenarios:

> The city works with other **partners**, such as contractors, transport agencies, police, highway suppliers, etc. who operate on the city's behalf. [I-MC-1]

The interworking of the city with its partners in addition to the citizen and their choice of daily solution providers is very complex. Hence, it is no surprise that in the digitalization phase thing will get worse, before it gets better: All stakeholders currently try to handle their own data, whilst discussing standard interfaces and protocols to exchange data. In the meantime data remains captive in technology and organizational silos.

> **All of these stakeholders** move towards systems that generate real-time data [that] is captured by **real-time data** generators, **smart devices**, but are **confined in closed systems**. [I-MC-1]

When compared with the solutions of big data or digital-born companies, such as Google, Amazon, Facebook etc. it becomes clear that the city requires platforms, maybe more similar to those of Airbnb or Uber, for the **intermediation between its users, the citizen, and its partners, the resource and infrastructure operators** on behalf of the city:

> So, the smart city will need to work with **platforms** on which data can be **analysed and shared** with other sources as well. [I-MC-1]

In the focus group workshop an interesting idea was raised, which is worth following up: When discussing the stakeholders and their relevant big data sources (see Figure 13) we actually identified that **mobility data may be the big data ecosystem nucleus that will bring most of the smart city stakeholders together**. The city and the citizens are mainly concerned with mobility and are willing to share their mobility data with technology providers if their service/solution can ensure reduction of unwanted traffic or reduction of travel times. Energy usage data currently has a very small originator base, namely the "involved citizens," who also care about other resources being used efficiently other than their time. **When mobility becomes increasingly electrified**, then energy data becomes part of the bigger ecosystem. Only then a cross-optimization of energy and mobility in terms of multimodal resources[194] becomes a possibility. However, without modern platform techniques, such complex and intertwined data flows as required in the digitalizing city, will essentially be broken.

2.4 MAIN TECHNICAL CHALLENGES

Urban data is not being sufficiently sourced, i.e. collected, or shared. Limits in data acquisition and inappropriate forms of storage limits the potential of full-fledged big data usage:

> The data is captured by real-time data generators, **smart devices, but** are **confined in closed systems**. [I-MC-1]

> Big data is seen as a commodity, although there are a lot of **proprietary systems** and **still Excel** tables as major form of data storage and sharing! [FG-TechPro]

> The data collected and reported is **very large grained**. What such installation **cannot account for** in a city are the **varying local aspects**, e.g. time of peak usage is different at different locations. [I-MC-1]

> **Oversupply of data is a definite need** for such technology drivers [like machine learning, big data computing]: the value creation only begins after certain richness and abundance has been achieved. [I-AI-1]

[194] S. Rusitschka et al, (2014) "Big Data meets Smart City – Optimization of Multimodal Flow Networks," VDE Congress 2014 - Smart Cities.

Whilst urban big data sources (see section 2.1) are increasingly being identified, such as social media, or rolled-out by the city and its partners, such as sensor data for mobility or energy efficiency, the **data still remains in silos or in old storage technologies or is not collected at high-resolution**. This is mainly **due to the "big data investment dilemma"** in cyber-physical systems: the one who invests in sourcing the data wants to reap value first – but big data value mainly materializes when it is merged and analysed at large-scale with many other sources and put to use in form of an action – maybe not even in the domain of the investor. As stated above, for reliable machine learning oversupply of data is even a basic requirement. The economical externality of this aspect is discussed in section 3.1. However, currently this is mainly seen as a technological challenge, because even if the investment dilemma was solved and the investors were willing to share the data, **how the data is being collected and stored massively influences how easily it can be shared**:

> Data, Services, and Systems are **not or only poorly integrated**, especially in **inter-city or international** scenarios, such as access to health services, or travel. [FG-Citizen]

> Today, the city interworking is mainly made up by entirely different and oftentimes **independent processes**, from traffic census to urban planning. However, the city is so complex that **brute force attitude to integrate** all processes at once inevitably fails. Instead, we would need a process of how everything can **grow together in evolutionary steps**. This was the case with the Internet, where **new platforms emerge** one after the other extending or replacing the previous. [I-AI-1]

> Now, it is more important to **be resilient** to **fast technological evolutions**, i.e. if a new and better storage technology is available, the platform and processes must enable to swiftly replace the old storage technology. There should be **no technology lock-in**. [I-MC-1]

Agility seems to be a common denominator. Even if the short-cut answer seems to be that all one needs is a big city "data lake"[195], there is not short-cut path to it. **Integrating big urban data will require evolutionary steps and accompanying platforms**. Building such platforms will need to take into consideration that in the short history of big data there have been disruptive technology waves every three years[196] changing the ways, data is being collected, stored, analysed an used.

Maintaining the privacy and security of the data being collected is also a very important challenge. Bottom line, it affects user acceptance – especially in the city:

> Nonetheless, there is the growing **unease of "we become transparent"** when using big data technology. [FG-City]

Different stakeholders need to be allowed access to different portions of the data being stored and collected and this security must be maintained at all levels of the network. The data must also be anonymised sufficiently so that the customers cannot be individually identified even after the data analysis. This is very difficult as the focus group findings as well as the following example show:

> Only four spatio-temporal points, approximate places and times, are enough to uniquely identify 95% of 1.5M people in a mobility database. The study further states that these

[195] http://en.wiktionary.org/wiki/data_lake

[196] http://byte-project.eu/wp-content/uploads/2014/09/BYTE_D1-4_BigDataTechnologiesInfrastructures_FINAL.compressed.pdf

> constraints hold even when the resolution of the dataset is low, mobility datasets and metadata circumvent anonymity.[197]
>
> **Anonymisation and security** are a challenge considering **algorithms that learn** (hidden) relationships within systems and about individuals through massive amounts of data coming from many sources. [FG-TechPro]
>
> Data **validation is a challenge**; however, benefits of solutions depend on it. [FG-TechPro]
>
> Current techniques in privacy and data protection, **the lack of transparency** also result in side-effects of security protocols, e.g. data access deadlock in case of a deceased person. [FG-Citizen]
>
> Current processes create **frictions when sharing data**; data **provenance and quality**, data **privacy and security** solutions are **not satisfactory**. [FG-City]

Nonetheless, creating user acceptance by assuring privacy and data security is essential for a sustainably digitalizing city. Of course, there is always the technically correct argument that when user benefits enough they will be willing to share their data no matter the privacy consequences such as with Facebook[198] or Google Maps for navigation. However, such an argument inevitably leads to social and ethical as well as regulatory externalities, which will be discussed in sections 3.2 and 3.3. The following is the opposing argument of "trustworthy structures" as a technical solution to this technical challenge:

> [...]We need structures, i.e. digital methods, which we trust; **trustworthy structures**. [...] In some instances this may translate that companies and individuals **use own structures**, **instead of uploading all data to** be managed by the knowledge graph of **Google**. These structures will impede data misuse; they will detect unintended use.[I-AI-1]

Smart city is a complex cyber-physical system of people, resources, and infrastructures. The creation of value from big urban data will require smart city platforms to mimic what big data natives are already capable of **cost-effective scalability and user experience**. For many technology providers this seems to be a challenge:

> **Scaling** algorithms and infrastructure with size and increasing demands for online and real-time. [F-TechPro]
>
> Creating the **right user experience** per stakeholder of a city platform. [F-TechPro]

An interesting implication of this technical challenge is that **big data currently represents a monopoly,** as the majority of technology providers active in the smart city domain are not capable of delivering both the scale and the user experience in such a complex setting as in the smart city, whereas big data native players, such as Google and Facebook operate at much greater scales also regarding the versatile stakeholders of their ecosystems, such as advertisers or social game companies. This implication as a legal and political externality is further discussed in sections 3.3 and 3.4.

---

[197] de Montjoye, Yves-Alexandre, César A. Hidalgo, Michel Verleysen, Vincent D. Blondel (2013, March 25): "Unique in the Crowd: The privacy bounds of human mobility". Nature srep. doi:10.1038/srep01376

[198] http://readwrite.com/2010/01/09/facebooks_zuckerberg_says_the_age_of_privacy_is_ov

2.5 BIG DATA ASSESSMENT

Smart cities are complex systems of resource infrastructures such as energy, transport, and information. The many stakeholders of a smart city ecosystem, from infrastructure to service providers to end users, require a common understanding of these complexities and the potential synergies. Only if synergies in resource usage across all interdependent infrastructure are leveraged, can the complexities associated with big data in smart cities be addressed, i.e. potentially massive amounts of data coming from intelligent infrastructures and especially always connected end users giving way to unnecessary data storage and potential profiling. Eventually, the city will require **platforms, which act as facilitators of digitalization and usage of data culminating in big data** as seen in the digital transformation of domains, such as content & media:

> City open data platforms, or federated open data portals, also enable digitalization and opening data of analogue sources like libraries. [FG-City]
>
> Building platforms, data aggregation, and building applications are the main creation and usage scenarios for technology providers. [FG-TechPro]
>
> So, the smart city will need to work with **platforms** on which data can be **analysed and shared** with other sources as well. [I-MC-1]

However, many cities do not yet have the organizational setup to create what is needed. Still there seems to be a disconnect between successful data-driven smart city pilots and their successful rollout. After the technological feasibility has been shown for a pilot use case, three questions still remain unanswered: (1) What is the operator model? (2) What are the business models? (3) Does it scale? These questions need new responsible city officials to answer, such as the Chief Data Officer created in many of US cities since 2011[199]:

> Cities are currently **not concerned** with Big Data and Cloud Computing as part of their **internal IT**. [I-MC-1]
>
> The City […] will have a Chief Information **Officer** for the **first** time. [I-MC-1]
>
> Only **one of the ten** local authorities is driving the pooling and interoperability of data sets. [I-MC-1]
>
> Big Data is seen as **commodity – but technologically not used as such,** since majority of existing solutions are **still proprietary** systems, or Excel-based, or can only be called **"somewhat open data" platforms**. [FG-TechPro]

In the recent years, the discussion around smart cities has shifted from a sole technological to a more user-oriented one. The increasing populations of the cities and how citizens are interacting with technology in their day-to-day life is demanding cities to make use of digitization. However, this is both a techno-economical as well as an organisational paradigm shift for cities as it has been for other sectors: Non-digital born sectors are just not used to "all data:"

> Oftentimes potential big data turns out to be "**tiny data**" due to the many **proprietary and incompatible** data sources, **invalid** data etc. [FG-TechPro]
>
> Traditionally, like many other sectors, cities have been managing **only the necessary data – not all data**. [I-MC-1]

[199] http://www.governing.com/blogs/bfc/col-city-chief-data-officers-performance-new-york-philadelphia.html

Nonetheless, cities can be seen as early majority in adopting big data technologies due to their commitment to enabling a better life, safer environment, which requires modernization, sensorisation and automation of non-digital infrastructures. The cross-optimization of energy and transport becomes possible when the multimodal networks are represented as a multilayer virtual network and combined with real-time data. This is the very definition of big data: a scenario, in which *high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making*[200].

> Today temporal data is rather used through large-grained patterns. In the future these temporal patterns will be much more **fine grained** to optimized also in (near) **real-time**, not only in planning. [I-MC-1]
>
> For aspects like air pollution, **individual sensors** only enable lose control. [FG-City]
>
> When more fine-grained information is needed with respect to **capturing temporal and spatial aspects**, big data computing is inevitable. [I-MC-1]

All one needs to look for in big data, so the argument goes, are more and more correlations vs. what we need to look for in big data can only ever be discovered through the lens of theory.[201] However, if the analytics should also give insights about what actions need to be undertaken, i.e., prescriptive analytics, then theory of system behaviour is absolutely necessary. At the same time the system may be changing in different ways than initial models can predict, hence a real-time monitoring of both data and model is necessary to capture so-called concept drift.

Data-driven analytics is required when dealing with data-rich but theory-poor domains such as online communities and neuroscience. The city, however, is a planned, constructed, and engineered system, consisting of increasingly digitized physical infrastructure. Models based on physical laws such as the flow network models use known external knowledge of the physical processes. At the same time, in today's complex systems and increasing dynamics through liberalized economic transactions, end user participation with their shared resources – e.g. cars to provide transportation, or PV installation to provide energy – numerical analysis to solve these models becomes very hard.

With model- and data-driven analytics, more data leads to better models, and better models lead to smarter data – enabling actionable knowledge without invading privacy or compromising confidentiality. These are all new frontiers, which will require years of research before producing feasible answers.

3 ANALYSIS OF SOCIETAL EXTERNALITIES

In the following we will present the societal externalities as collected and analysed after the focus group workshop and interviews. Each subsection starts with a table of the findings followed by a brief discussion. The statements that lead to a finding are quoted in the same manner as described in section 1.1. Each finding related to an externality is coded as defined in the case study methodology of EU BYTE. This will enable the cross-analysis of the different case studies conducted in BYTE to form a sound basis for the policy and research roadmaps for Europe. The codes can also be found in Table 55 of this deliverable.

[200] http://www.gartner.com/it-glossary/big-data
[201] http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory

3.1 ECONOMICAL EXTERNALITIES

Table 51 Economical externalities of big data in a digitalizing city

Code	Quote/Statement [source]	Finding
E-OO-BM-2	[I-MC-1] The data is captured by real-time data generators, smart devices, but are confined in closed systems. So, the smart city will need to work with **platforms** on which data can be **analysed** and **shared** with other sources as well. [FG-TechPro] There are **no incentives for data sharing** required at that big scale. [I-MC-1] For example, the city [...] is currently developing a smart card infrastructure for transportation. Although the bus system is deregulated, becoming part of the **ecosystem is advantaEarthObvsus** for the bus companies.	Need for data sharing favours forms of concentration like platforms, ecosystems. These concentration forms are hard to kick-start at the scale of a complex system such as the city.
E-OO-BM-5	[I-MC-1] **Cities** are not businesses, i.e. the return on investment will not be given by **scaling**. A **contractor** company working with a city can do this, i.e. create a working solution for one city and sell it to the next with minimal or no changes. [I-MC-1] the **size of the market** matters. Just one city does not offer a big enough market to create a significant market pull. So, in UK, six or seven, cities group together to procure new technology. In contrast, China has such huge infrastructure projects. And because of that scale, **standards** come from there. [...] Much of the innovation happens in US, because the market is so huge.	Given the complex interrelations in a city, building big data structures for it requires a size. The size of the market determines technology standards for the rest.
E-OO-TEC-1	[I-MC-1] **Investment** into data infrastructures, not only sensorisation but also data collection and storage, will be similar to investments into a new shopping centre. They need an "**anchor tenant**," such that people will travel to go there. [I-MC-1] The transportation card needs a digital infrastructure **investment**, free Wi-Fi in busses etc. However, the city needs to ensure **interoperability**. [I-MC-1] There is the cultural issue about how one perceives innovation and R&D: A lot of companies are **sitting on their money**, instead of looking for new ways to invest. [I-AI-1] Oversupply of data is a definite need for such technology drivers: the value creation only begins after certain richness and abundance has been achieved [...] There are opponents to this view. However, this opposition may also originate from the **lack of willingness to invest**.	Investments by the private sector need to be secured by reduction or compensation of future uncertainties. Otherwise the current state of lack of investments will remain.
E-OC-TEC-2	[FG-TechPro] There is **immense efficiency increase potential** along the dimensions of time, costs, and resources. [I-AI-1] The entire **supply** system in a city, from mail to groceries is **inefficient** [...]: the single drives to malls, the many stops of the same mail delivery companies sometimes multiple times a day, etc. In our digitalizing days, we have	The final return on investment through efficiency gains compared to the current non-digitalized utilities and processes is

	[...] the ability to **bundle** through digital controls and **intermediation**.	undisputed.
E-OC-LEG-3	[FG-TechPro] Funding or **monetization is challenging**, even if technology is feasible and potential benefits can be quantified. [I-IA-1] We have to measure by the use of data: then the data generator, the end user, can**not receive money for the raw data**. For example, Amazon uses the transactional data of its users to optimize and create efficiency gains, which then are reflected in better offers. The **benefit** of the raw data **only** materializes, **when it is used and value is created**, which penetrates through to the end user. We have to measure by the use of the data, **not by its source, collection, or storage**. [I-AI-1] the type of machine learning algorithms we are using combines and melts data to find insights, underlying structures within data, which are useful. After such use the **raw data is not even traceable** [...] to pay for the raw data would be equally foolish. [I-IA-1] **Facts and data cannot be copyrighted**; hence environmental data captured by sensors surrounding us should be open. [FG-City] Data ownership by private sector	Monetization of big data remains a moving target. Strong arguments against short-term business model of data marketplaces. Data ownership seems to be a faulty concept, on which we build laws and businesses.
E-PC-DAT-1 E-OC-DAT-2	[I-IA-1] It is an intricate question then why would anyone want to invest into this data infrastructure. The answer is more complex, but there may be two components to it: (a) it is also part of the **investment to facilitate** the fast and good usage of data (b) the owner of the data infrastructure is allowed **to reap value first but opens the data after that**, similar to scientific use of data. [I-MC-1] If such [statistical] data were **opened, also small businesses** could afford to analyse it, and answers can be derived down on a much more focused and local level. [I-AI-1] The **investment into a data infrastructure must be a centre piece in the city**. Once the infrastructure is in place and used by the city administration and stakeholders, maybe co-investors, then that data should be opened: they represent facts about the city. When opened**, much more value** can be created **by the masses of "urban hackers" and start-ups**, which will naturally be **drawn to such cities**. [FG-City] **Data-savvy cities** offer economic benefits to the **new digital sector**, and hence increase the **city's welfare**. [I-AI-1] The **secure usage** of data can **ignite new business models** in the digital world, similar to secure money transport. The machine learning algorithms used for fraud detection with credit cards for example do give trust. Loss of trust is loss of business.	In case of the digital city, big data investment dilemma can be solved: Investment by the public sector into the data infrastructure of a city and the subsequent opening of this infrastructure as a utility/commodity will create a win-win for all, ignite new business and increase welfare.

E-OO-BM-3	[I-MC-1] With the **current process of procurement**, the **incentive** is only on choosing the **cheapest technology**. [I-MC-1] [...] new trends are beginning to emerge within cities: **open innovation**, **open procurement** to free from long period and rigid supplier contracts. In these changing environment, cities require more **flexibility** and working in **ecosystem** of providers. Recently, the Open and Agile Cities initiative was launched. [I-MC-1] Many initiatives now prefer the **OpenStack** approach. It is definitely a **new mindset**, compared to the **old "one-supplier-vertical-integration"**. [I-MC-1] There is a vast area to **mandate interoperability**, through best practice and requirements sharing, e.g. for new sensor technologies. The European Commission basically has [new] mechanisms for that. However, **large companies rely on old ways of procurement**, and this might be a risk to them.	Old incentives are being overthrown, putting large companies relying on these old structures at high risk.
E-OC-BM-5	[I-AI-1] [...] benefits will outweigh the traditional business case of not investing in such a data infrastructure, e.g. keep **counting cars at street corners by men** sitting on chairs the whole day.	Old jobs are at risk.
E-OC-BM-3	[FG-City] Cities require data capability team or sustainability teams with analytics views in order to create more value-ass from available data. There are already cities employing city analytics managers. [FG-TechPro] App developers	New skills are required and create new jobs.

The need for data sharing favours forms concentration like platforms and ecosystems on through which the costs of data acquisition, curation, storage, and analyses cab be shared by the many stakeholders. This may be true for other sectors, however, we believe that these concentration forms are hard to kick-start at the scale of a complex system such as the city. Although quasi-monopolistic and not preferable in the long-run, building big data structures requires a certain size. The size of the market determines technology standards for the rest. There is a new trend also followed by the cities that **open source and open platforms might be an answer to create the favoured forms of concentration without the monopolistic structures**. Hence, for the digital city, it seems, the big data dilemma may be easier to solve: **Investment by the public sector into the data infrastructure** of a city and the subsequent **opening of this infrastructure as a utility/commodity** will create a win-win for all, ignite new business and increase welfare.

The final return on investment through efficiency gains compared to the current non-digitalized utilities and processes is undisputed. Nonetheless, monetization of big data remains a moving target. Investments by the private sector need to be secured by reduction or compensation of future uncertainties, otherwise the current state of lack of investments will remain. **Short-term business models which do not take technology peculiarities into account are risky: Data marketplaces for example**, not only ignore that raw data in itself has no value, but also with advanced machine learning algorithms to create value from massive amounts of raw data, that it is very hard to track raw data for billing or for

prosecuting copy-right infringements. Regarding the reduction of uncertainties: Clearing ambiguities of copyright[202] in the era of big data and open data should also be the utmost purpose of a *new legal framework*, as also briefly discussed in section 3.3. **Data ownership seems to be a faulty concept, on which we build laws and businesses.**

In general, old incentives, such as through current procurement processes, are being overthrown, putting large companies relying on these old structures at high risk. Similarly, with the increasing potential of machines that learn[203]old jobs consisting of simple tasks are also at risk. New skills are required and create new jobs, but numbers are most likely not equal – also see discussion in the following section.

3.2 SOCIAL & ETHICAL EXTERNALITIES

Table 52 Social & Ethical Externalities in a digitalizing city

Code	Quote/Statement [source]	Finding
E-OC-BM-5	[I-AI-1] benefits will **outweigh the traditional** business case of not investing in such a data infrastructure, **e.g. keep counting cars at street corners by men** sitting on chairs the whole day.	As a society we are responsible to find answer to the new question: what will men do when machines learn simple tasks?
E-PC-ETH-1	[I-AI-1] It is not long before we will see the creation of further **utilities of care** [groceries, mail, health services], as we are used to with gas, water, electricity etc. [I-MC-1] [...] analogies, e.g. there are regulations about how you use land, but not on how you build houses on that land – which results in wrong type of houses being built. Instead, here should be **tighter regulation on what to build as indicated by the need for it** – and less on regulations on how to use the land, i.e. we want **social aspects to be the driver** etc.	Socially desirable outcomes must be formulated first. Foster research into big data for social good – especially in the digitalizing city.
E-OC-ETH-7 E-CC-ETH-1	[FG-City] **Invisible sensors** in a digitalizing city raise trust issues. [I-AI-1] In the same way we trust the computer-assisted mechanisms today, such as autopilot in a plane, we can **trust computing methods**, which will prevent malpractice in data collection and sharing. [FG-Citizen] Data-driven apps are welcome when useful, but the feeling that one "**gives away too much" of themselves** is increasing through increasing use and debate of personal or urban data.	Trust in computing methods for big data may be harder to establish because big data enables the understanding, optimization, and improvement also of individuals.
E-OC-ETH-1 E-PC-ETH-2	[FG-Citizen] Data-driven technologies that can give citizens "heads up" **make life easier**, and the **city more liveable**. Out of hours services save vain trips that **saves time and**	Big data in a digitalizing city has immense potential

[202] "Copyright does not protect facts, data, or ideas though it does protect databases." http://www.lib.umich.edu/copyright/facts-and-data

[203]https://www.ted.com/talks/jeremy_howard_the_wonderful_and_terrifying_implications_of_computers_that_can_learn

	resources. [FG-Citizen] Data-driven apps enable **informed and secure** travel, **better planning**, or increase the ability of responsiveness as a user of infrastructures and services in case of disturbances, avoidance of mass panic and decision making under stress, which can **save lives**.	for creating social good.
E-OC-ETH-4	[FG-Citizen] **Low-income** citizens can enjoy **same or similar offerings** in a city through the comparison web sites, and service specific sites. [FG-Citizen] **Profile-based pricing** of services, and risk-based business models have **negative impact on people right to equality.** [FG-City] Cities must also **take care of the non-digital**, be it citizens or infrastructures, e.g. backup non-digital, digital divide.	All data is created equal, but utilizing data-driven services will create new debate on assuring "enough" equality.
E-OO-DAT-4	[FG-Citizen] Internet-access and apps **cost, which prevents** some citizens from enjoying the same offers as the rest. [FG-Citizen] **Trustworthy information, lack of efficiency gain information, or aggressive** ads can **prevent from usage** of data-driven services.	There are many different reasons why not all citizens will reap the value.

The **potential of big data to be used for social good is immense especially in the digitalizing city**[204]. However, there is a range of pitfalls, we, as a society, need to take care of: The immense reliance on data-driven services will **need a new debate on how we can assure "enough" equality**, when there are **so many different reasons why not all citizens will reap value from data in equal amounts**. This may be due to the digital divide we have been aware of for a while now, or to entirely new challenges through recent technological breakthroughs such as *deep learning*, which enable machines to learn and take over simple tasks, such as counting cars or recognizing letters. As a society we are responsible to find the answer to the new question: "what will men do when machines learn simple tasks?" **Trust** in computing methods for big data may be harder to establish because **big data enables the understanding, optimization, and improvement also of individuals**. Socially desirable outcomes must be formulated first.

3.3 LEGAL EXTERNALITIES

Table 53 Legal externalities of big data in digitalizing cities

Code	Quote/Statement [source]	Finding
E-OO-TEC-1	[I-AI-1] It is **foolish to believe** raw data can and should be **protected by a data police**: the type of machine learning algorithms we are using combines and melts data to find insights, underlying structures within data, which are useful. After such use the data is not even traceable – if you will: **machine learning can protect privacy**. [FG-City] **Algorithms define what will be found**, e.g. in	For the same reasons[205] to open crypto-algorithms, machine learning algorithms must be open sourced.

[204] http://www.hsph.harvard.edu/ess/bigdata.html
[205] https://www.schneier.com/crypto-gram/archives/1999/0915.html

	case of libraries being digitalized and indexed as with search engines would mean that popular literature easier to find than rare – which is opposing to the foundation of libraries.	
E-PO-LEG-1 E-PC-LEG-4	[I-MC-1] Also with transactional data, there are not many surprises to be found in the data. As an example from insurance companies, who mainly collected and managed master data, insights cannot really be gained but rather facts can be reported about. In comparison, **mobile phone data** has a **lot of metadata** that can help in extracting new insights, especially when **correlated with other data**. However, it also requires **peoples' permission and understanding of dat**a. [I-MC-1] **Regulatory frameworks** [...] are **changing, breaking down**. [I-MC-1] In the past we have seen that well **regulated companies have advantages**: take the car manufacturer business in Japan versus US. The car manufacturing was a lot about materials, safety, and supply chains. If we think of data as a good/resource as well then regulation might help companies to turn these resources into value in a more sustainable way. [I-MC-1] there is the **ideological split** whether there should be **more or less regulation**. It depends on the level and on who is being regulated. In all of these decisions the **citizens should be put first**. [I-MC-1] [...] regulation must also be **against special interest protectionism** of incumbents and new players alike, and instead put citizen first. [I-AI-1] In Germany, we have the principal of data minimization that opposes the technical need of data abundance. Data minimization is seen as the principal to grant privacy. Data privacy should really **protect the individual instead of sacrificing opportunities by avoidance**. [I-AI-1] There is the other principal of informational self-determination, which is a basic right of an individual to determine the disclosure and use of her personal data. Again there is the misunderstanding: **each piece of data originates through us**, like leaving footprints on the beach. We have to ask ourselves: so what? And only if there is a **practical – not a theoretic – threat to privacy invasion**, only then measures must be taken. These countermeasures, the **penalties of data misuse, must be so high that they will prevent misuse.** [I-AI-1] the cities should invest and open up, and hence facilitate the explosion of creativity, without angst, without data avoidance. In order to cultivate such a perspective, **the full force of the law** must be brought to bear in taking action **against data misuse.**	New sources of data create new ways that data can be misused – our legal framework needs an upgrade, with the core principal of putting the individual first.

E-PC-LEG-3	[I-AI-1] **At the end all data**, be it of natural language- or sensor-origins, is usage data – hence **originating from the user**. We need to step back from the definition of data and data carrier. [I-AI-1] Privacy threat is created by **abuse of data not the use of data**. You still trust the bank with your money even though there is potential of a robbery or other forms of abuse. Bottom line is, we should not interfere too early: data collection and sharing should be facilitated. [I-AI-1] The past NSA affair showed that is utopian to think that data misuse can be prevented. Instead we need structures, i.e. digital methods, which we trust; **trustworthy structures**. We have to stay clear from avoidance structures [...] These structures will **impede data misuse**, they will **detect unintended use**, and **laws must be in place to severely punish misuse**.	Put the citizen first, not her data, when wanting to protect.

New sources of data create new ways that data can be misused. We are in need of a **new legal framework** with the **core principal of putting the individual first**. Data ownership seems to be a faulty concept, on which we build laws and businesses. In addition, with big data computing, **machine learning algorithms which prescribe actions** as derived through that data become a centre-piece: Businesses, critical infrastructures, and lives may rely on these actions and as such these algorithms must become public. The **same understanding of open source and security in the cryptography domain**[206] **should apply** to machine learning domain. Either we wait until this understanding also established in the big data domain, or the new and digitally literate legal frameworks come with these transitive best practices already built-in.

In turn, this argument has an *economic externality*, since almost any business working with data today, mostly considers data but especially the algorithms that create value from this data as their intellectual property and competitive advantage. It may well be that, at the end of this big data paradigm shift, we realize that **data as well as algorithms to mine the data are required commodities** to create value through user experience and services.

Another major point regarding legal externalities was made in the discussion of economic externalities of how **big data structures favour monopolistic forms of concentration** (see 3.1). Here the analogy of "**data as a resource**" again turns out to be very suitable. Because turning data into value requires special skills and technologies that are currently concentrated at a few digital-native companies, these companies can be considered to expose monopolistic structures. Whilst in other domains, the typical legal answer is liberalization – in technology-driven domains, this does not work effectively[207]. On the other hand, favouring of **open source** in order for other companies to be able to use same technologies, may be a very **suitable instrument in the data economy to open monopolistic structures.**

[206] https://www.schneier.com/crypto-gram/archives/1999/0915.html

[207] Liberalization of metering business in Europe still is lagging, because the technology of smart metering still lacks viable business cases and cost-effective technology.

3.4 POLITICAL EXTERNALITIES

Table 54 Political externalities of big data in digitalizing cities

Code	Quote/Statement [source]	Finding
E-OC-LEG-1 E-OC-LEG-2	[I-MC-1] There is a transitional relationship between public sector, universities, and industry. [...] However, large international companies do have local presences; many selling **web-based, digital products and services**. So, all three, the public, industry, and universities, can be all in different nations –digitalization is in a sense **great for mobilizing the European market** to become as interesting to innovators. [FG-TechPro] **Data location** determines which legislation, since there is **no unified data legislation** in Europe, this makes scaling a data-driven business very difficult – due to the many adaptations with respect to **small national markets**. [I-MC-1] There is no big market in Europe compared to US. **But with respect to infrastructure**, e.g. mobile telecommunications market, Europe is **much better connected**.	Big data business can weaken European economy, if big data monopoly of companies like Google, Amazon, etc. remains. Big data business can improve European economy, but requires a unified European data economy with accordingly unified policies. Policymaking should build on digitalizing already strong European physical infrastructures.
E-PC-ETH-1	[I-MC-1] At EC level we rather need coordination and not restriction. And this **coordination also should put citizens first**. [FG-City] Personalized, i.e. **citizen-centric**, policy-making and services **with immediate feedback become possible for the first time**.	Policy makers should take advantage of digitalization and use the potential of big data for policymaking.

The "economies of digital" blur the boundaries we know from the non-digital world: a city, national or EarthObvsgraphic boundaries. The challenge of "small markets" was also mentioned in the economical externalities discussion in Section 3.1 followed by the evidence that European cities are starting to **leverage the "economies of digital" to their advantage**. Instead of feeling neglected by technology providers who require a substantial market pull, they form so-called agile open cities initiatives to create market pull. Similarly policy making for Europe needs to take the lead in creating a substantial market pull by creating **a unified European data economy with accordingly unified policies**. European policymaking should also focus on build on digitalizing already strong European physical infrastructures through the cities.

"No infrastructure – whether it is a road, a building, a broadband network or an intelligent energy grid – will have a transformative effect on a city unless it engages with individuals in a way that results in a change of behaviour"[208]. As also concluded in the focus group discussions: "Personalized, i.e. **citizen-centric**, policy-making and services **with immediate feedback become possible for the first time**." Policy makers should take advantage of digitalization and use the **positive potential of big data for policymaking**.

[208] http://theurbantechnologist.com/2012/08/13/the-amazing-heart-of-a-smarter-city-the-innovation-boundary/

4 CONCLUSION

The smart city case study on the societal externalities of big urban data captured some interesting insights through the analysis of a focus group workshop findings and interviews. The illustrative user stories with a few examples of new smart city initiatives such as “the linked city” or “participatory sensing” exhibit typical big data characteristics of integrating the variety of available and new data sources, or creating higher volume, higher velocity data through increased sensorisaton and its use for real-time optimizations. Although some European cities can be seen as early majority to adopting big data, organizational and cultural changes will still be required to create value from big urban data in a sustainable way.

There is the typical big data investment dilemma also in the cities, however, an investment by the public sector into the data infrastructure of a city and the subsequent opening of this infrastructure as a utility/commodity can create a win-win outcome for all stakeholders. Open source and open platforms seem to be an answer to create the favoured forms of concentration without the monopolistic structures that are characteristic of the current big data players. The potential of big data to be used for social good is immense especially in the digitalizing city. However, there is a range of pitfalls, we, as a society, need to take care of: The strong reliance on data-driven services will need a new debate on how we can assure “enough” equality, when there are so many different reasons why not all citizens will reap value from data in equal amounts. Trust in computing methods for big data may be harder to establish because big data enables the understanding, optimization, and improvement also of individuals. Socially desirable outcomes must be formulated first. Personalized, i.e. citizen-centric, policy-making and services with immediate feedback become possible for the first time. Policy makers should take advantage of digitalization and use the positive potential of big data for policymaking for the European cities.

APPENDIX A: LIST OF SOCIETAL EXTERNALITIES CONSIDERED

Table 55 List of societal externalities considered

Code	+/-	Stakeholders	Main topic	Description
E-PC-BM-1	+	Public sector-citizens	Business models	Tracking environmental challenges
E-PC-BM-2	+	Public sector-citizens	Business models	Better services, e.g. health care and education, through data sharing and analysis (need to explain the benefits to the public)
E-PC-BM-3	+	Public sector-citizens	Business models	More targeted services for citizens (through profiling populations)
E-PC-BM-4	+	Public sector-citizens	Business models	Cost-effectiveness of services
E-PC-DAT-1	+	Public sector-citizens	Data sources and open data	Foster innovation, e.g. new applications, from government data (data reuse)
E-PC-LEG-1	+	Public sector-citizens	Policies and legal issues	Transparency and accountability of the public sector
E-PC-LEG-2	-	Public sector-citizens	Policies and legal issues	Compromise to government security and privacy (due to data sharing practices)
E-PC-LEG-3	-	Public sector-citizens	Policies and legal issues	Private data misuse, especially sharing with third parties without consent
E-PC-LEG-4	-	Public sector-citizens	Policies and legal issues	Threats to data protection and personal privacy
E-PC-LEG-5	-	Public sector-citizens	Policies and legal issues	Threats to intellectual property rights (including scholars' rights and contributions)
E-PC-ETH-1	+	Public sector-citizens	Social and ethical issues	Increased citizen participation
E-PC-ETH-2	+	Public sector-citizens	Social and ethical issues	Crime prevention and detection, including fraud (surveillance using big data)
E-PC-ETH-3	-	Public sector-citizens	Social and ethical issues	Distrust of government data-based activities
E-PC-ETH-4	-	Public sector-citizens	Social and ethical issues	Unnecessary surveillance
E-PC-ETH-5	-	Public sector-citizens	Social and ethical issues	Public reluctance to provide information (especially personal data)
E-PC-TEC-1	+	Public sector-citizens	Technologies and infrastructures	Gather public insight by identifying social trends and statistics, e.g. epidemics or employment rates (see social computing)
E-PC-TEC-2	+	Public sector-citizens	Technologies and infrastructures	Accelerate scientific progress (improved efficiency in data access, improved data analysis)
E-OC-BM-1	+	Private sector-citizens	Business models	Rapid commercialization of new goods and services
E-OC-BM-2	+	Private sector-citizens	Business models	Making society energy efficient
E-OC-BM-3	+	Private sector-citizens	Business models	Data-driven employment offerings
E-OC-BM-4	+	Private sector-citizens	Business models	Marketing improvement by using targeted advertisements and personalized recommendations
E-OC-BM-5	-	Private sector-citizens	Business models	Employment losses for certain job categories (white-collar jobs being replaced by big data analytics)
E-OC-BM-6	-	Private sector-citizens	Business models	Risk of informational rent-seeking
E-OC-BM-7	-	Private sector-citizens	Business models	Reduced market competition (creation of a few dominant market players)

E-OC-BM-8	-	Private sector-citizens	Business models	Privatization of essential utilities (e.g. Internet access)
E-OC-DAT-1	+	Private sector-citizens	Data sources and open data	Enhancements in data-driven R&D
E-OC-DAT-2	+	Private sector-citizens	Data sources and open data	Fostering innovation from opening data
E-OC-DAT-3	+	Private sector-citizens	Data sources and open data	Time-saving in transactions if personal data were already held
E-OC-DAT-4	-	Private sector-citizens	Data sources and open data	Creation of data-based monopolies (platforms and services)
E-OC-LEG-1	+	Private sector-citizens	Policies and legal issues	Increased insight of goods (more transparency)
E-OC-LEG-2	+	Private sector-citizens	Policies and legal issues	Increased transparency in commercial decision making
E-OC-LEG-3	-	Private sector-citizens	Policies and legal issues	Private data accumulation and ownership (losing control of their personal data)
E-OC-LEG-4	-	Private sector-citizens	Policies and legal issues	Threats to intellectual property rights
E-OC-ETH-1	+	Private sector-citizens	Social and ethical issues	Safe and environment-friendly operations
E-OC-ETH-2	+	Private sector-citizens	Social and ethical issues	Increase awareness about privacy violations and ethical issues of big data
E-OC-ETH-3	-	Private sector-citizens	Social and ethical issues	Invasive use of information
E-OC-ETH-4	-	Private sector-citizens	Social and ethical issues	Discriminatory practices and targeted advertising (as a result of profiling and tracking private data)
E-OC-ETH-5	-	Private sector-citizens	Social and ethical issues	Distrust of commercial data-based activities (due to lack of transparency or unintended secondary uses of data)
E-OC-ETH-6	-	Private sector-citizens	Social and ethical issues	Unethical exploitation of data, e.g. some types of tracking and profiling, encompassing concerns about discrimination and dignity (especially relevant in sensitive domains such as health or finance)
E-OC-ETH-7	-	Private sector-citizens	Social and ethical issues	Consumer manipulation
E-OC-ETH-8	-	Private sector-citizens	Social and ethical issues	Private data leakage (concern about data protection and cyber threats, especially bankcard fraud and identity theft)
E-OC-ETH-9	-	Private sector-citizens	Social and ethical issues	Private data misuse, especially sharing with third parties without consent
E-OC-ETH-10	-	Private sector-citizens	Social and ethical issues	Privacy threats even with anonymised data (easy to de-anonymise) and with data mining
E-OC-ETH-11	-	Private sector-citizens	Social and ethical issues	Public reluctance to provide information (especially personal data)
E-OC-ETH-12	-	Private sector-citizens	Social and ethical issues	"Sabotaged" data practices
E-OC-ETH-13	-	Private sector-citizens	Social and ethical issues	Lack of context or incomplete data can result in incorrect interpretations
E-OC-TEC-1	+	Private sector-citizens	Technologies and infrastructures	Free use of services, e.g. email, social media, search engines
E-OC-TEC-2	+	Private sector-citizens	Technologies and infrastructures	Optimization of utilities through data analytics
E-CC-ETH-1	-	Citizens-citizens	Social and ethical issues	Continuous and invisible surveillance
E-CC-TEC-1	+	Citizens-citizens	Technologies	Support communities

			and infrastructures	
E-OO-BM-1	+	Private sector-private sector	Business models	Opportunities for economic growth through community building (sharing information and insights across sectors)
E-OO-BM-2	+	Private sector-private sector	Business models	Innovative business models through community building (sharing information and insights across sectors)
E-OO-BM-3	-	Private sector-private sector	Business models	Challenge of traditional non-digital services, e.g. new data-driven taxi and lodgement services
E-OO-BM-4	-	Private sector-private sector	Business models	Monopoly creation through the purchase of data-based companies
E-OO-BM-5	-	Private sector-private sector	Business models	Competitive disadvantage of newer businesses and SMEs (creation of a few dominant market players)
E-OO-BM-6	-	Private sector-private sector	Business models	Reduced growth and profit among all business, particularly SMEs (creation of a few dominant market players)
E-OO-DAT-1	-	Private sector-private sector	Data sources and open data	Inequalities to data access (digital divide between big data players and the rest)
E-OO-DAT-2	-	Private sector-private sector	Data sources and open data	Dependency on external data sources, platforms and services (due to dominant position of big players)
E-OO-DAT-3	-	Private sector-private sector	Data sources and open data	Threats to commercially valuable information
E-OO-DAT-4	-	Private sector-private sector	Data sources and open data	Distrust on data coming from uncontrolled sources
E-OO-ETH-1	-	Private sector-private sector	Social and ethical issues	Market manipulation
E-OO-TEC-1	-	Private sector-private sector	Technologies and infrastructures	Barriers to market entry (due to dominant position of big players, the need for major investment, and the complexity of big data processing)
E-PO-BM-1	+	Public sector-private sector	Business models	Opportunities for economic growth (new products and services based on open access to big data)
E-PO-BM-2	+	Public sector-private sector	Business models	Innovative business models (closer linkages between research and innovation)
E-PO-DAT-1	-	Public sector-private sector	Data sources and open data	Open data puts the private sector at a competitive advantage (they don't have to open their data and have access to public data)
E-PO-DAT-2	-	Public sector-private sector	Data sources and open data	Inequalities to data access, especially in research (those with less resources won't be granted access to data)
E-PO-LEG-1	-	Public sector-private sector	Policies and legal issues	Lack of norms for data storage and processing
E-PO-LEG-2	-	Public sector-private sector	Policies and legal issues	Reduced innovation due to restrictive legislation
E-PO-ETH-1	-	Public sector-private sector	Social and ethical issues	Taxation leakages (intermediation platforms, delocalization of data-based corporations)
E-PP-LEG-1	-	Public sector-public sector	Policies and legal issues	EarthObvspolitical tensions due to surveillance out of the boundaries of states
E-PP-LEG-2	-	Public sector-public sector	Policies and legal issues	Need to reconcile different laws and agreements, e.g. "right to be forgotten"

APPENDIX B: PROGRAM OF THE BYTE WORKSHOP ON BIG DATA IN OIL & GAS

Big data in oil & gas workshop
Telenor Arena (VIP/Main entrance), Meeting room A (third floor)
Widerøeveien 1, Fornebu (Oslo)
16 April, 9:00 – 13:00

Agenda

9:00 – 9:15	**Welcome and introductions** Roar Fjellheim, Computas AS
9:15 – 9:45	**Talk I: Big data in subsea – the operator view** Knut Sebastian Tungland, Soil
9:45 – 10:30	**Results of the BYTE case study in Oil & Gas** Guillermo Vega-Gorgojo, Universitetet i Oslo
10:30 – 10:45	**Coffee break**
10:45 – 12:00	**Small group discussions: big data in oil & gas, applications, challenges and impacts** • What additional types of data might be useful for or associated with oil & gas data? What are some of the technological processes that underpin the analysis of these data? • What additional applications or impact areas might result from analysing data in oil & gas? • To what extent do the potential positive impacts described here match with your experience or the possibilities you envision? • To what extent do the potential challenges and negative impacts discussed here match with your experience? How have you and your colleagues worked to address these? How successful has this been? **Report back to larger group**
12:00 – 12:30	**Talk II: Big data in subsea – the supplier view** Hege Kverneland, National Oilwell Varco
12:30 – 12:45	**Closing remarks** Arild Waaler, Universitetet i Oslo
13:00 – 14:00	**Lunch**

APPENDIX C: PROGRAM OF THE BYTE FOCUS GROUP ON BIG DATA IN THE ENVIRONMENT SECTOR

Meliá Vienna, Donau City Strasse 7
1220 Vienna, Austria
13 April, 12:00 – 17:00

Agenda

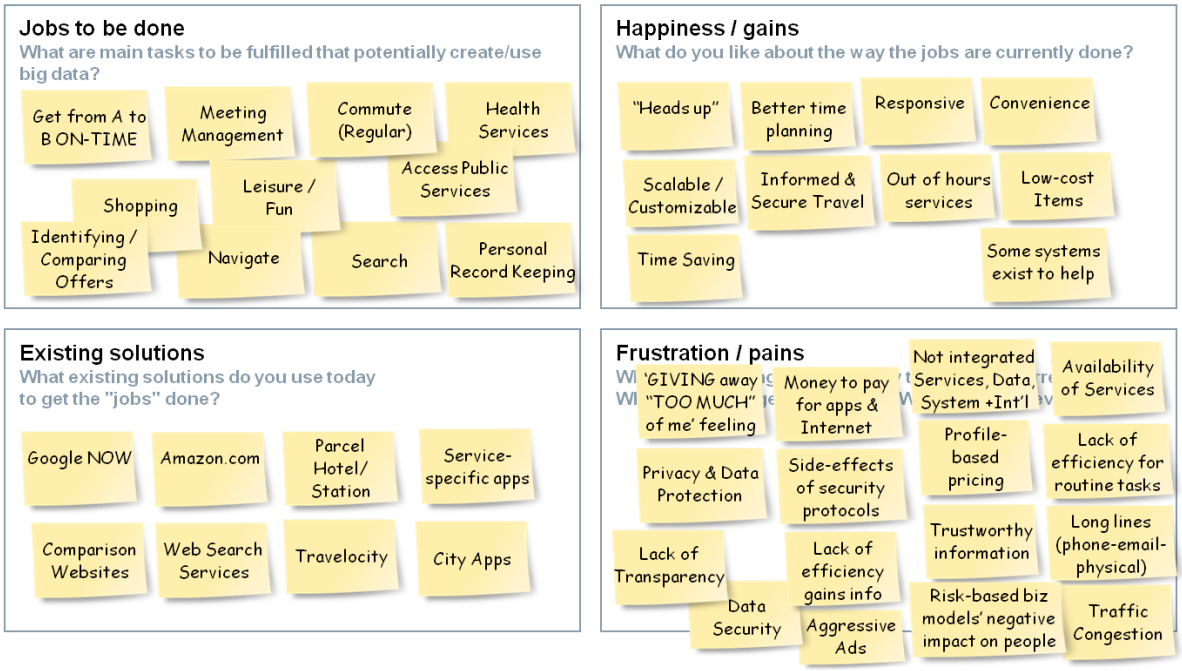
12:00-13:00	**Lunch**
13:00 – 13:30	**Welcome and introductions** Lorenzo Bigagli, National Research Council of Italy
13:30 – 15:00	**Small group discussions: Big environmental data technologies and applications** • What are the potential values, to all who might benefit, of exploiting the "data super nova" in the environment sector? • What e-infrastructure (i.e. technological processes, data sources, key actors, and policies) is needed to facilitate the full exploitation of big environmental data? **Report back to larger group**
15:00 –15:15	**Coffee break**
15:15 – 16:45	**Small group discussions: Positive and negative impacts of big environmental data** • What factors (internal/external, technical/non-technical) may hinder getting the most out of the environmental data super nova to maximize societal benefits, in your experience, or with the possibilities you envision? • What factors may instead facilitate getting the most out of the environmental data super nova to maximize societal benefits? • How have you and your colleagues worked to address these? How successful has this been? **Report back to larger group**
16:45 – 17:00	**Closing remarks** Lorenzo Bigagli, National Research Council of Italy

APPENDIX D: PROGRAM AND OUTCOMES OF THE BYTE FOCUS GROUP ON BIG DATA IN THE SMART CITIES SECTOR

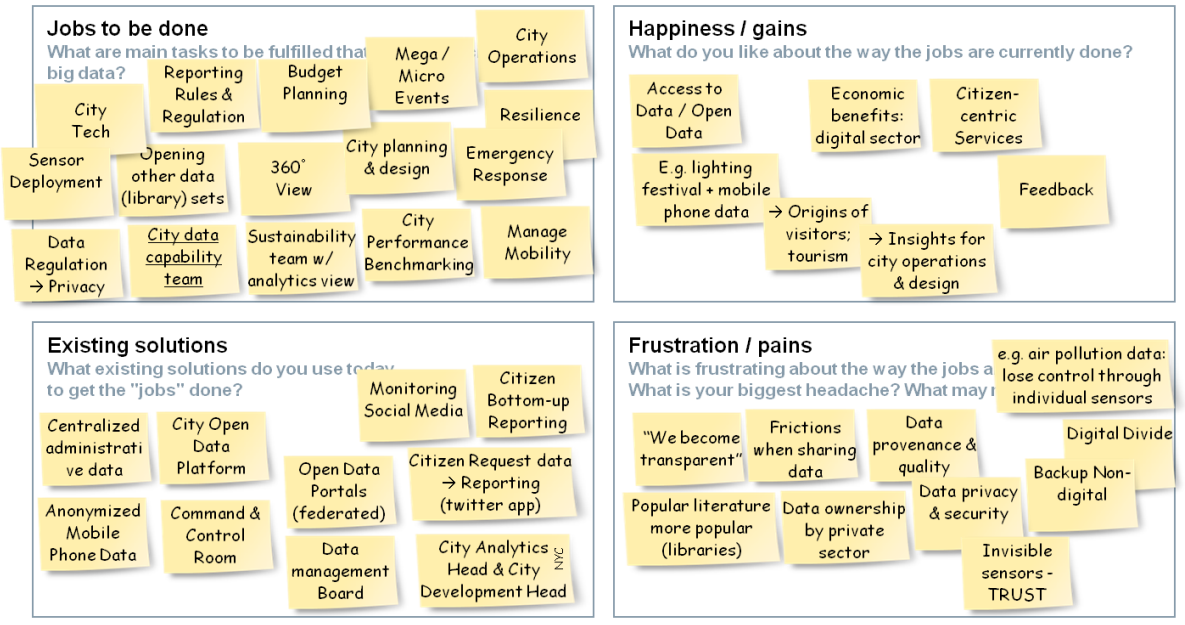
Agenda

10:00 – 10:30	**Introduction Round (all)** *Professional and Personal Perspective on Big Data in a Digital City*
10:30 – 11:00	**Stakeholder Review (all)** *Who are the people and businesses that create urban data, create data-driven offerings, who benefits, who is at risk – when?*
11:00 – 12:30	**Analyze Stakeholders' Demands (break-out session)** *Anticipate the future needs of the people and businesses in an increasingly digitalizing city "full of data"*
12:30 – 13:15	Lunch Break
13:15 – 14:30	**Value and Innovation Spaces (break-out session)** *A walk in their shoes: where do they meet their needs, how does the environment look like, which creates gains and relieves pain with data*
14:30 – 15:00	**Touch Points for the Focus Group in the Future (all)** *How can you as thought leaders w.r.t. Big Data in Digital – Smart – Cities help create and meet the people in such value and innovation spaces*

Stakeholder View: Citizen



Stakeholder View: City



Stakeholder View: Technology Provider