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DOI
10.1080/10919392.2015.1125180

Publication date
2016

Document Version
Accepted author manuscript

Published in
Journal of Organizational Computing and Electronic Commerce

Title page

Journal of Organizational Computing and Electronic Commerce (JOCEC)

Article for special issue “Advances in big and open data”

Article title:

Improving the speed and ease of open data use through metadata, interaction mechanisms and quality indicators

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Abstract

The usage of Open Government Data (OGD) has not kept pace with the expectations as existing OGD infrastructures mainly serve as data repositories. Many OGD infrastructures do not stimulate or support OGD use processes, and there is a lack of research regarding which functionalities can stimulate such processes. The objective of this study is to use a design science approach to evaluate whether metadata, interaction mechanisms and data quality indicators can improve OGD use. OGD use comprises five main activities, namely searching for and finding OGD, OGD analysis, visualizing OGD, interacting about OGD, and OGD quality analysis. We expect that three OGD key infrastructure elements – metadata, interaction mechanisms, and data quality indicators – allow for improving these five OGD use activities. A prototype of an advanced OGD infrastructure was created which implements the three OGD infrastructure elements. Three quasi-experiments with a pre-test post-test control group design were conducted. The quasi-experiments showed that the prototype facilitated the usability of the novel OGD use functionalities. Our quasi-experiments supported our propositions that metadata, interaction mechanisms, and data quality indicators contribute to making OGD use easier and faster, and enhance the user experience. The infrastructure elements improved OGD use by better enabling searching, analysing, visualizing, discussing, giving feedback on and assessing the quality of open data. Hence, we plea for integrating metadata, interaction mechanisms, and data quality indicators in open data infrastructures to advance open data usage.

Keywords: open data, open government data, e-government, usability, adoption, use, metadata, interaction, social media, quality, quasi-experiment, design research

1. Introduction

Open Government Data (OGD) use is still in its infancies. A first wave of OGD infrastructures provides only basic functionalities for uploading and downloading data (Alexopoulos, Spiliotopoulou, and Charalabidis 2013, Charalabidis, Loukis, and Alexopoulos 2014), whereas merely providing access to information is not enough for actively involving open data users (Jurisch et al. 2015). Existing OGD infrastructures have shortcomings such as the limited provision of information about the context in which the data have been created (Alexopoulos, Spiliotopoulou, and Charalabidis 2013), the limited opportunity for open data users to participate in improving published data (Alexopoulos, Spiliotopoulou, and Charalabidis 2013) (e.g. through cleaning and processing and through social media discussions), and the ranging data quality (Auer et al. 2013, Kuk and Davies 2011, Petychakis et al. 2014).

As a consequence, there is a feeling that OGD is not yet showing its full potential (Jetzek, Avital, and Bjorn-Andersen 2014, Novais, Albuquerque, and Craveiro 2013, Jetzek 2015), and the use of open datasets is low (Bertot, McDermott, and Smith 2012, Jurisch et al. 2015). At the same time, it has been argued that the next generation of OGD infrastructures may help to overcome a number of barriers for OGD use (Charalabidis, Ntanos, and Lampathaki 2011, Zuiderwijk 2015). OGD infrastructures may make it easier to use OGD, and in this way they may stimulate the adoption of open data and contribute to attaining the objectives of governmental open data policies. Nevertheless, there is a lack of research regarding which functional elements of OGD infrastructures can stimulate OGD use. The objective of this study is to use a design science approach to evaluate whether three functional elements (metadata, interaction mechanisms and data quality indicators) can improve OGD use.

This article is organized following the common phases of design science research. Design science research (for example, Peffers et al. 2008, Hevner et al. 2004, March and Smith 1995) in essence suggests to start with the identification of the problem, which will be done in the following section. Subsequently, objectives of a solution should be identified, which will be done in section three encompassing an overview of potential functional elements for an OGD infrastructure derived from the literature. The design and development of an artefact (building), as well as the evaluation of the artefact are other subsequent elements that design science research commonly incorporates (March and Smith 1995). In section four we describe the design of the OGD infrastructure prototype that was created as part of this research, and thereafter the evaluation approach and results are presented in sections five and six. Finally, conclusions regarding the usefulness of the functional OGD infrastructure elements are drawn.

2. Open data use and OGD infrastructures

Despite the availability of a large number of datasets, OGD use is still low (Bertot, McDermott, and Smith 2012, Jurisch et al. 2015). An OGD infrastructure can be defined as "a shared, (quasi-)public, evolving system, consisting of a collection of interconnected social elements (e.g. user operations) and technical elements (e.g. open data analysis tools and technologies, open data services) which jointly allow for OGD use" (Zuiderwijk 2015, 45). To identify which OGD infrastructure elements may improve OGD use, we used the literature to generate an overview of the activities that OGD use comprises. The literature suggests that OGD usage activities can be divided into five main categories, namely searching for and finding OGD, OGD analysis, OGD visualisation, interaction about OGD and OGD quality analysis (see Table 1).

OGD use category	**Examples**	**References**
Searching for and finding OGD	Browsing, querying and exploring datasets	Auer et al. (2013), Charalabidis, Ntanos, and Lampathaki (2011), Kuk and Davies (2011), Petychakis et al. (2014)
OGD analysis	Statistical analysis	Kuk and Davies (2011), Charalabidis, Ntanos, and Lampathaki (2011)
	Transforming data	Charalabidis, Ntanos, and Lampathaki (2011)
	Viewing data online	Petychakis et al. (2014)
	Downloading data	Alexopoulos, Spiliotopoulou, and Charalabidis (2013)
OGD visualization	Generating plots, maps, graphs	Charalabidis, Ntanos, and Lampathaki (2011)
	Interactive dataset representations	Lindman, Kinnari, and Rossi (2014)
Interaction about OGD	The use of feedback from end users as training input	Auer et al. (2013), Bertot, McDermott, and Smith (2012)
	Collaboration through discussion forums, messaging, user groups and other functionalities	Charalabidis, Ntanos, and Lampathaki (2011)
OGD quality analysis	Analysis and assessment of the dataset quality	Auer et al. (2013), Charalabidis, Ntanos, and Lampathaki (2011)

Table 1: A categorization of OGD use.

Next, an overview of the major factors which hinder these types of OGD use activities is made. The latter is used to select the main activities that we will improve. The literature reveals many factors that complicate each of the five identified OGD use activities. With regard to *searching for and finding OGD* the literature shows that locating existing OGD is complex and accompanied with high costs (Ding, Peristeras, and Hausenblas 2012). Data are offered at many different places (Braunschweig et al. 2012a, Conradie and Choenni 2014, De Vocht et al. 2014), and can sometimes be hard to find (Conradie and Choenni 2014, Braunschweig et al. 2012a). Open data are fragmented by default (De Vocht et al. 2014). Moreover, each discipline has its own terminology which leads to heterogeneity (Reichman, Jones, and Schildhauer 2011). Different terms and vocabularies are often used to describe open datasets (Yannoukakou and Araka 2014). Furthermore, search options of many open data infrastructures are limited (Petychakis et al. 2014). In addition, Ho and Tang (2001) found that available data and information may become overwhelming in general. Also in the case of open data increasing amounts of data may lead to the situation in which open data users receive too much information. More and more governmental datasets are becoming available for public reuse (Sieber and Johnson 2015), and this may lead to the situation in which open data users receive too much information. In sum, it was found that factors hindering searching for and finding OGD are mainly related to data fragmentation, terminology heterogeneity, a lack of search support and information overload.

As far as *OGD analysis* is concerned, open datasets may be used for other purposes than those that they were created for initially. Dawes, Pardo, and Cresswell (2004) found that reusing information collected for one purpose for other purposes may potentially result in misuse, misunderstanding, and misinterpretation. This equally applies to the open data field, as open data can be reused for other purposes than they were collected for originally. The fear of drawing false conclusions from open data use is commonly mentioned (Conradie and Choenni 2014). Moreover, Alexopoulos, Spiliotopoulou, and Charalabidis (2013) note that open data infrastructures traditionally do not provide contextual information for the offered datasets. This poses a problem, since a large part of the population lacks knowledge of the context of these data (Foulonneau, Martin, and Turki 2014). In addition, Braunschweig et al. (2012a) posit that the analysis of data requires the use of different tools. At the same time, Novais, Albuquerque, and Craveiro (2013) point at the lack of tools to generate information that can easily be understood by the population. Moreover, it has been argued that most traditional open data infrastructures only supply basic data download and upload functionalities instead of more advanced data analysis tools (Alexopoulos, Spiliotopoulou, and

Charalabidis 2013, Charalabidis, Loukis, and Alexopoulos 2014). The lack of support for data analysis might influence to which extent OGD can be analysed effectively. In conclusion, we argue that OGD analysis is influenced by the data context, the extent of data interpretation support, data heterogeneity and data analysis support.

Regarding *OGD visualization*, several scholars have stated that visualization tools are useful (De Vocht et al. 2014) or even necessary for using open data (Shadbolt et al. 2012). For instance, visualization tools based on maps can be used to obtain insight in datasets. O'Hara (2012) and Alani et al. (2008) specifically point at the importance of maps for making sense of data. Open data visualizations may facilitate the processes in which non-expert users discover and analyse data, find links between them and obtain insights (Dimou et al. 2014). However, the literature also shows that OGD visualization functionalities are barely provided to OGD users by existing OGD portals (Sayogo, Pardo, and Cook 2014, Liu, Bouali, and Venturini 2014). Thus, complexities related to data visualization are mainly influenced by a lack of data visualization support.

With regard to *interaction about OGD*, the delivery of open data is characterized by a lack of opportunity for public participation and engagement (Sieber and Johnson 2015). For instance, conversations about released data are lacking (idem). Such conversations are also lacking for used data. Moreover, many OGD providers do not know who their external users are (Archer et al. 2013). Feedback mechanisms can be used for interaction about OGD. However, Archer et al. (2013) posits that even if feedback mechanisms are offered, this type of feedback is characterized by informal communications as part of institutional collaborations, comments on blogs and replies to Tweets. Most governmental agencies do not offer feedback mechanisms for open data (Alexopoulos, Spiliotopoulou, and Charalabidis 2013, Archer et al. 2013). In addition, most open data infrastructures traditionally do not facilitate the improvement of opened data (e.g. through cleaning and processing) (Alexopoulos, Spiliotopoulou, and Charalabidis 2013). We argue that interaction about OGD is affected by two key factors, namely a lack of interaction and a lack of interaction support and tools.

Finally, as far as *data quality analysis* is concerned, the literature shows that data quality plays an essential role in the use of government portals (Detlor et al. 2013). A certain level of data quality is essential for OGD use. Yet, the quality of data varies widely (Kuk and Davies 2011, Petychakis et al. 2014). Users may be concerned about the quality of open data (Martin 2014) and open data often suffer from poor quality, such as inconsistency in terms used in datasets and a lack of granularity (Kuk and Davies 2011). Since open data can be reused over time, this can easily affect the quality of the data (Oviedo, Mazon, and Zubcoff 2013). Issues related to the *poor quality* of open data can be a major issue (Karr 2008, Whitmore 2014). In sum, the literature shows that OGD quality analysis is influenced by factors related to the dependence on the quality of open data, poor data quality, and quality variation and changes. Table 2 summarizes the identified OGD use categories and the identified factors hindering OGD use.

OGD use category	**Factors hindering OGD use**
Searching for and finding OGD data	Data fragmentation
	Terminology heterogeneity
	Search support
	Information overload
OGD analysis	Data context
	Data interpretation support
	Data heterogeneity
	Data analysis support
Visualizing OGD	Data visualization support
Interaction about OGD	Lack of interaction
	Interaction support and tools
OGD quality analysis	Dependence on the quality of open data
	Poor data quality
	Quality variation and changes

Table 2: Overview of factors hindering OGD use.

3. Functional elements of the OGD infrastructure

Section two showed that many factors influence and complicate the five identified types of OGD use, while this section identified objectives of a solution. The five types of OGD use may be improved through an OGD infrastructure. Propositions for the design of the OGD infrastructure were created in collaboration with partners from the ENGAGE-project, which was a combination of a Collaborative Project and Coordination and Support Action (CCP-CSA) funded by the European Commission under the Seventh Framework Programme. A design proposition can be defined as “a general template for the creation of solutions for a particular class of field problems” (Denyer, Tranfield, and van Aken 2008, 395). The design propositions suggest on a high level which functional infrastructure elements may be used to improve OGD use. For the next generation of OGD infrastructures, we propose three key elements to improve OGD use, namely metadata, interaction mechanisms and data quality indicators. Although there may be other ways to deal with the hindering factors, these infrastructure elements were found to be critical. The following design propositions were generated:

- Proposition 1: Metadata, interaction mechanisms and data quality indicators positively influence the ease of OGD use in the five identified OGD use categories.
- Proposition 2: Metadata, interaction mechanisms and data quality indicators positively influence the speed of OGD use in the five identified OGD use categories.

In the remainder of this section we discuss the different aspects of these design propositions. First, although successful OGD use can be measured through various aspects (e.g. satisfaction, efficiency, or effectiveness), this study focuses on the ease and speed of OGD use. This was done because we endorse the idea that ease and speed of OGD use are the basis for successful OGD use. If OGD use would be very difficult, or if it would take considerable time, we believe that the satisfaction of OGD users will not be high. Likewise, the efficiency and effectiveness of OGD use is not expected to be high if ease and speed of OGD use are insufficient.

Second, metadata may assist in organizing a diversity of content sources, managing content and describing resources (Duval et al. 2002). Metadata can assist in describing, locating and retrieving resources efficiently and may improve their accessibility (Joorabchi and Mahdi 2011). At the same, time metadata provision for open data is often cumbersome (Martin 2014). The literature postulates that it is essential for the correct interpretation and use of open data to offer sufficient metadata simultaneously to data (Jeffery 2000, Braunschweig et al. 2012b) We propose metadata as a mechanism to improve all the five types of OGD use, including searching for and finding OGD, OGD analysis, OGD visualization, interaction about OGD, and assessing the quality of OGD.

Third, different types of interaction mechanisms may affect to which extent users can interact on OGD infrastructures and can engage and collaborate. The interaction between open data providers and users in OGD processes may be stimulated through various functionalities. For example, Dawes and Helbig (2010) and Bertot, McDermott, and Smith (2012) suggest the development of formal feedback mechanisms. Since users may discover and correct errors in the data and communicate such errors and improvements to the data provider and other data users, this type of feedback may lead to continuous improvements to datasets of benefit to all future users of the dataset (Dawes and Helbig 2010). Moreover, public agencies can profit from user feedback and engage the public in agency operations to asses which data the public desires and to respond to queries (Bertot, McDermott, and Smith 2012). Existing social media may be used to engage people in open datasets

(Garbett et al. 2011) and to facilitate openness and transparency efforts (Stamati, Papadopoulos, and Anagnostopoulos 2015).

Finally, the literature overview showed that open data success depends strongly on the quality of released datasets (Behkamal et al. 2014). OGD reuse requires that potential data users can trust that datasets which they want to use are of sufficient quality (O'Hara 2012). However, the quality of open data can easily be affected because of the reuse of the data (Oviedo, Mazon, and Zubcoff 2013). At the same time the quality of data varies widely (Kuk and Davies 2011, Petychakis et al. 2014), and also depends on the purpose that one has for the reuse of an open dataset. The quality of OGD may be too low to use them for certain purposes. It is therefore important that OGD users can obtain more insight in the quality of OGD that they want to use.

After the design propositions had been created, we developed design principles to guide the design efforts. Whereas the design propositions had been described on a relatively high level of abstraction, the design principles further refined the design input. Gilb (1997, 165) defines principles as “rules of thumb that guide the choices and actions of engineers”. A literature review regarding metadata, interaction and data quality was conducted to elicit design principles. Examples of elicited design principles are: ‘metadata facilitate the integration of data and information from heterogeneous sources’ (Jeffery 2000), ‘the integration of existing social media may facilitate the engagement of people with open data’ (Garbett et al. 2011), and ‘information about the nature of datasets and about factors that determine data quality support the assessment of data quality’ (Dawes 2010). Based on the elicited design principles, the functional design of the OGD infrastructure was described. The design of the infrastructure is an iterative process, and various iterations took place between the functional design of the OGD infrastructure and the design principles. Examples of defined functions are ‘upload dataset’, ‘request data’, and ‘assess or examine structured data quality ratings’. A selection of these functions was implemented in the prototype design, as described in the following section.

4. Prototype design

Prototyping refers to building a working version of various aspects of a system (Bernstein 1996). To be able to evaluate the three OGD infrastructure elements and to further refine the user requirements, a prototype of the infrastructure was developed which was called ‘ENGAGE’. The prototype was constructed as part of the ENGAGE-project, which was a combination of a Collaborative Project and Coordination and Support Action (CCP-CSA) funded by the European Commission under the Seventh Framework Programme. Almost all the functions that we had defined in the functional design were selected for implementation in the prototype, except for 'convert data format', 'refer to data', 'link data manually', 'enter an open collaboration group', 'enter a closed collaboration group' and 'compare different quality ratings and reviews'. These six functions were not implemented due to time limitations, because using these functions in the evaluations would be too time-consuming, and because these three functions are not central to the five OGD use activities of searching for and finding OGD, OGD analysis, OGD visualization, interaction about OGD and OGD quality analysis. Table 3 provides an overview of the functionalities implemented in the prototype. Screenshots of the prototype are provided in Appendix A.

OGD infra-structure element	**Prototype functionality**	**Functionality description**
Metadata	Upload dataset	Anyone can upload a dataset.
	Enhance metadata	Anyone can add metadata.
	Acquire datasets	Users can use a single point of access to acquire datasets from various OGD infrastructures. The infrastructure harvests datasets from different governmental OGD infrastructures.
	Acquire metadata	Users can acquire metadata. The infrastructure can harvest metadata from different governmental OGD infrastructures.
	Retrieve data by query	Datasets can be queried through the SPARQL Protocol and RDF Query Language (SPARQL) and through the Structured Query Language (SQL).
	Retrieve data by facets	Facetted search is possible so that datasets can be ordered in multiple ways through filters desired by the user, e.g. they can be filtered or ordered by geospatial and temporal coordinates, the country where the data comes from, data categories (e.g. environment, finance or education), the data publisher and the dataset license. Controlled vocabularies are integrated.
	Retrieve data by keywords	Users can enter a simple keyword to find datasets.
	Search multilingually	The infrastructure translates the keywords from the original language to various other languages, resulting in multilingual search results.
	Request data	Data users can request governmental agencies or other OGD users to open a certain dataset that they cannot find through the infrastructure.
	Download data	Datasets can be downloaded to the personal computers of users.
	Obtain a structured metadata overview	An overview of discovery, contextual and detailed metadata is visible to the user (e.g. the dataset maintainer, date of last update, dataset release date). The metadata are described following existing standards.
	Display data services	For each dataset it is shown which processing services are available.
	Obtain a multilingual	All the available information about the dataset is automatically

	dataset overview	translated to the language entered by the user.
	Viewing the dataset online without downloading	Datasets can be viewed and explored online without the need to download the data. Interactive views, such as the Excel Online Web Application can be used for this.
	Create an extension graph and manage different versions of datasets	Users can see hierarchically how an extended or derived dataset relates to the original dataset and how the original dataset was reused. When a dataset has been extended (e.g. when metadata are added to it or when additional formats of the same dataset are added), users can see a graph of the extensions, as well as the type of extension.
	Cleanse data	For each dataset it will be shown which services are available to cleanse datasets (e.g. using Open Refine).
	Enhance metadata	After data analysis users are encouraged to supply additional metadata.
	Obtain license information	Metadata are provided about the license for reusing a dataset.
	Visualise data in a table	For each dataset it will be shown which services are available to visualise datasets in tables (e.g. through the Excel Online Web Application).
	Visualise data in a chart	For each dataset it will be shown which services are available to visualise datasets in charts (e.g. through the Excel Online Web Application).
	Visualise data on a map	For each dataset it will be shown which services are available to visualise datasets with geographical variables on maps.
	Register a user and create a profile	Users can register (e.g. with one of their social media accounts) and create a profile.
	Search through user profiles	CERIF provides the feature to provide metadata describing users.
	Follow user	Users may subscribe for following the activities conducted by another user.
	Follow dataset	Users may subscribe for following datasets so that they receive a notification when the dataset had been changed or updated.
	Obtain overview of interaction tools	For each dataset it will be shown which tools are available to provide feedback on the dataset, to discuss the dataset, and to collaborate in data use.
	Obtain data quality metadata	Contextual metadata is provided about the dataset, the person who created it and other contextual aspects. This allows OGD users to evaluate their confidence in the data quality and in the data provider.
Interaction mecha-nisms	Request data	OGD users can request datasets from governmental organisations and from other OGD users
	Provide feedback to data providers	OGD users can provide feedback to governmental organisations and to other OGD users (e.g. concerning errors in the dataset).
	Provide feedback to policy makers	OGD users can provide feedback derived from the use of the dataset (e.g. policy recommendations and contributions to decision making) to other OGD users and to governmental organisations.
	Submit related items	Users can submit an item related to the original dataset (e.g. a publication that was written based on the dataset, a report about the data collection method or a visualisation or application of the dataset).
	Write a message to discuss data or data use	Users can post a message to discuss a dataset or to discuss conclusions based on data use (e.g. users can describe how they used a dataset and what they learned from this). For each message it is visible who posted it.
	Write a personal message	Users of the infrastructure can send each other personal messages that are delivered in the form of e-mails.

	Obtain community overview	Users of the infrastructure can obtain an overview of all the users registered on the OGD infrastructure. The profiles of OGD providers, OGD users and policy makers can be searched, e.g. by keyword, pre-defined organisations or user group.
	Post Wiki articles	Users can post articles about open data use in general (so not related to particular dataset) on a Wiki. For example, the Wiki contains documentation and tutorials about how the infrastructure can be used to visualise and curate datasets.
	Share data or data use findings on social media	Users can share a dataset or findings from data use via social media (e.g. Twitter, Facebook, LinkedIn). Social media are integrated in the OGD infrastructure to allow for building online networks of OGD providers, OGD users and policy makers.
OGD quality indicators	Assess or examine structured data quality ratings	Users can assess or examine the quality of a dataset on pre-defined quality dimensions.
	Obtain an overview of the distribution of ratings	Users can obtain information about how the quality ratings of the dataset are distributed.
	Write a free text review of the data quality	Users can discuss or they can view a discussing on the quality of a dataset. Users can write a review and describe the purpose for which the dataset was used.
	Obtain quality evaluator information	A selection of background information about the evaluator of the data quality was visible to all users of the infrastructure.

Table 3: Overview of the implemented prototype functionalities.

A four-tier architecture was implemented in the prototype, including a user interface layer, a presentation logic layer, a business logic layer and a data access layer. The user interface layer contained the user interface components for the external interfaces, and was used for the communication between end-users and the rest of the system. The presentation logic layer supported workflows for user activities on the ENGAGE prototype and the provision of meaningful information to users of the prototype. In the business logic layer business logic decisions, data processing and process scheduling were enabled, while the data access layer provided access to stored data underlying the user activities.

5. Evaluation methodology: Quasi-experiments

This section aims to evaluate the OGD infrastructure elements that were discussed in section three. The evaluation aimed at examining to which extent the functional infrastructure elements can improve OGD use. In the following sections the evaluation approach and structure using three quasi-experiments with a pre-test post-test control group design are described.

5.1 Quasi-experimental approach

We aimed to evaluate the developed prototype in a realistic setting in which participants had to operate the prototype, and at the same time we wanted to control the variables to test our propositions and to ensure that the effects could be attributed to metadata, interaction mechanisms, and data quality indicators. Experiments can be conducted to manipulate variables and observe their effects upon other variables (Campbell and Stanley 1969, 2). An experiment can be defined as "a study in which an intervention is deliberately introduced to observe its effects" (Shadish, Cook, and Campbell 2002, 12), and can be either a *true experiment* or a *quasi-experiment*. Quasi-experiments encompass 1) a treatment and a control condition, 2) a pre-test and a post-test, and 3) a model that reveals the treatment and the control group effects over time, given no treatment effects (Kenny 1975). In quasi-experiments researchers can have control over selecting and scheduling measures, how the participants are assigned non-randomly, over the type of control group with which the treatment group is compared, and over how the treatment is organized (Shadish, Cook, and Campbell 2002). Since it was not possible for our evaluations to randomly assign participants to treatment and control groups, we cannot refer to the evaluations as a true experiments (Campbell and Stanley 1969). Therefore we conducted quasi-experiments. Figure 1 shows the variables involved in the quasi-experiments.

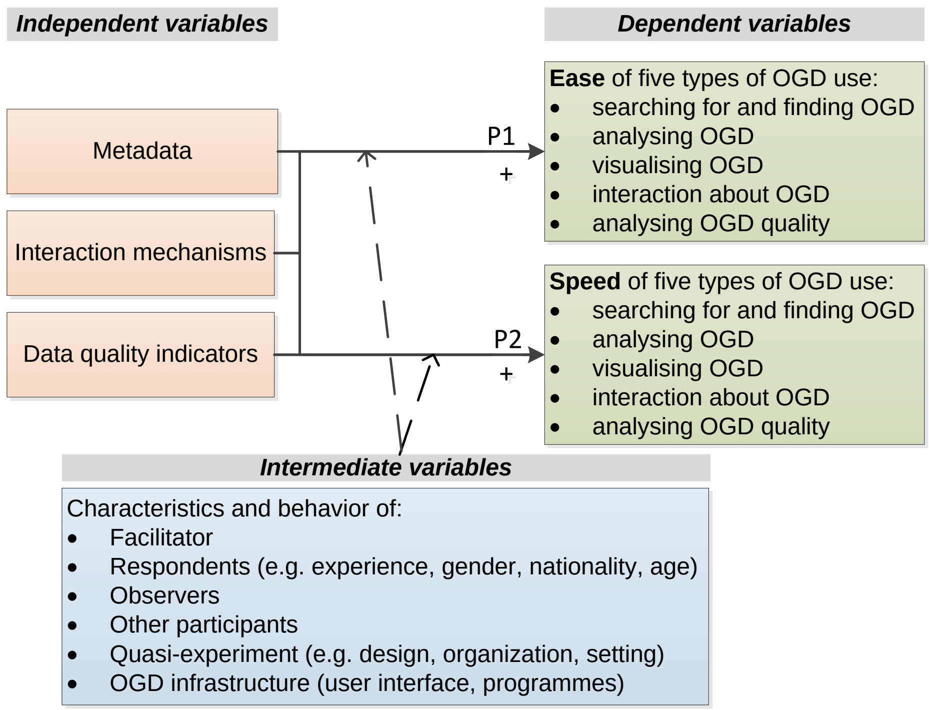

Figure 1: Overview of the variables involved in the quasi-experiments.

Table 4 lists the key characteristics of the quasi-experiments. Two groups of participants participated in the quasi-experiments, namely students and professional open data users. For the students, the quasi-experiments were part of a mandatory course, while the professionals participated in the quasi-experiments as part of a workshop on open data in which they participated voluntarily.

Quasi-experiment characteristic	**Description**	**Implementation**
Number of quasi-experiments	Multiple quasi-experiments can be conducted to see whether replicating the evaluations would provide the same results	- Three quasi-experiments in March and April 2014 - Involved 19 third year Bachelors students (QE1), 72 first year Masters students (QE2), and 36 professional open data users (QE3) - Quasi-experiments lasted between 95 and 100 minutes - Located at Delft University of Technology
Treatment and control group	A treatment and a control group can be used to investigate rival explanations for the findings and to enhance internal validity (i.e. the establishment of a causal relationship, showing that certain conditions lead to other conditions (Yin 2003))	- Participants of the first and second quasi-experiment were randomly split into a treatment group (i.e. a group that used the designed prototype) and a control group (i.e. a group that used a control OGD infrastructure) - Allowed for variation in the participants' use of metadata, interaction mechanisms and data quality indicators - Participants from the control group were not matched to a participant in the treatment group (see Reichardt 1979 for more information about matching), because the group of potential participants available for the evaluations was not large enough to find sufficient participants that could be matched pair-wise - Non-pair wise comparison of the control and treatment group was performed
Pre-test and post-test	Rival explanations can be investigated by using a pre-test post-test design (Verschuren and Hartog 2005), which may enhance internal validity	- A pre-test post-test design was used: we measured at least once just before the artefact was used and once just after it was used
Intermediate variables	Intermediate variables may influence the effect of the independent on the dependent variables (Pearl 2001), and it is not clear whether this influence actually exists and what its nature is	- Six intermediate variables were examined: the role of the facilitator, characteristics of the respondents (e.g. experience with OGD use), the role of the observers, other participants, the design, organization and setting of the evaluation (e.g. the room and sounds), the infrastructure (e.g. the user interface and the available programs) - Searched for patterns by investigating various characteristics of the treatment and control group as a whole (e.g. investigated the distribution of participants within certain age categories and OGD experience, and compared them for the different groups)
Inclusion criteria	Inclusion criteria are the predefined characteristics that qualify potential participants for including them in the study (Salkind 2010),	Inclusion criteria were: - Participants had to have the skills to work with computers - Participants had to be at least 20 years old - Participants had to have attended presentations concerning the basics of open data - Participants had to live in the Netherlands - Participants had to be available for the quasi-experiments

	may enhance internal validity	and be willing to participate in the evaluations
Non-equivalent groups	Non-randomly designed groups can be referred to as non-equivalent groups (Campbell and Stanley 1969)	- Not possible to randomly select a sample of participants, since there is no central overview of people who belong to the population of OGD users from which we can randomly draw such a sample - Could not randomly assign participants to the treatment and control group, although they could choose themselves where they were going to sit in the room, which determined the group that they would be part of. The participants did not know in advance that their seat determined in which group they would participate
Using multiple sources of evidence	Triangulation can be used to study topics from multiple perspectives, obtain richer information and a 'fuller' picture (Myers 2013), enhances construct validity (i.e. the establishment of correct operational measures for the concepts that are investigated (Cronbach and Meehl 1955))	- Multiple sources of evidence were combined: quantitative surveys and time measures were combined with qualitative semi-structured participant observations - Survey questions were based on a model developed by Venkatesh et al. (2011) which integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) and the two-stage expectation confirmation theory of Information Systems (IS) continuance (expected to enhance the external validity, i.e. the establishment of the domain to which the findings of the research can be generalized (Yin 2003))
Scenario based design	Scenarios were incorporated: narrative descriptions of interactions between users and proposed systems (Potts 1995)	- Participants had to operate the OGD infrastructure before we could ask for their experiences. Since it was not possible to find examples of functioning OGD infrastructures in practice which contained the three infrastructure elements, merely using surveys or interviews to ask people for their experiences with such OGD infrastructures would not result in the desired type of outcomes - Evaluations consisted of a practical session in which the participants worked with the OGD infrastructure by conducting scenario tasks
Protocols and instructions	Reliability can be enhanced by developing protocols and instructions	- The evaluation facilitator received detailed instructions in a training session - An observation protocol was developed, provided to the observers, and explained to them in a training session - Observers were provided with a semi-structured observer survey - Similar pre-test and post-test surveys were used in all evaluations for both the treatment and the control group to enhance reliability - Scenario tasks and instructions were similar in all evaluations

Table 4: Overview of the characteristics of the quasi-experiments.

5.2 Treatment versus control condition

Three groups were given two different infrastructures to test the effect of the introduction of metadata, interaction mechanisms, and data quality indicators. Quasi-experiments were conducted with three groups to ensure that sufficient participants were involved and that the responses to the questionnaire could be analysed with statistical tests. The other conditions for the treatment groups and the control group remained as equal as possible. The metadata model of the control OGD infrastructure described datasets in Dublin Core fields with additional options from Qualified Dublin Core. These standards are mainly focused on discovery metadata and provide limited information about the context of datasets (Zuiderwijk 2015). Metadata fields that were mandatory to complete were title, creator, date created, description, access rights, date available, and audience. Optional metadata fields include contributor(s), subject, spatial coverage, temporal coverage, source, identifier, format, relation, language, and remarks (The Data Seal of Approval Board 2013). The control OGD infrastructure allowed for several functionalities related to metadata that the treatment OGD infrastructure also supported, although usually in a more limited way. For instance, tools for visualizing data in tables were available for a limited number of datasets. The treatment OGD infrastructure provided more metadata fields in various categories, and incorporated contextual and detailed metadata, whereas these types of metadata were barely provided by the control infrastructure. Figure 2 provides an overview of the metadata fields incorporated in the treatment OGD infrastructure.

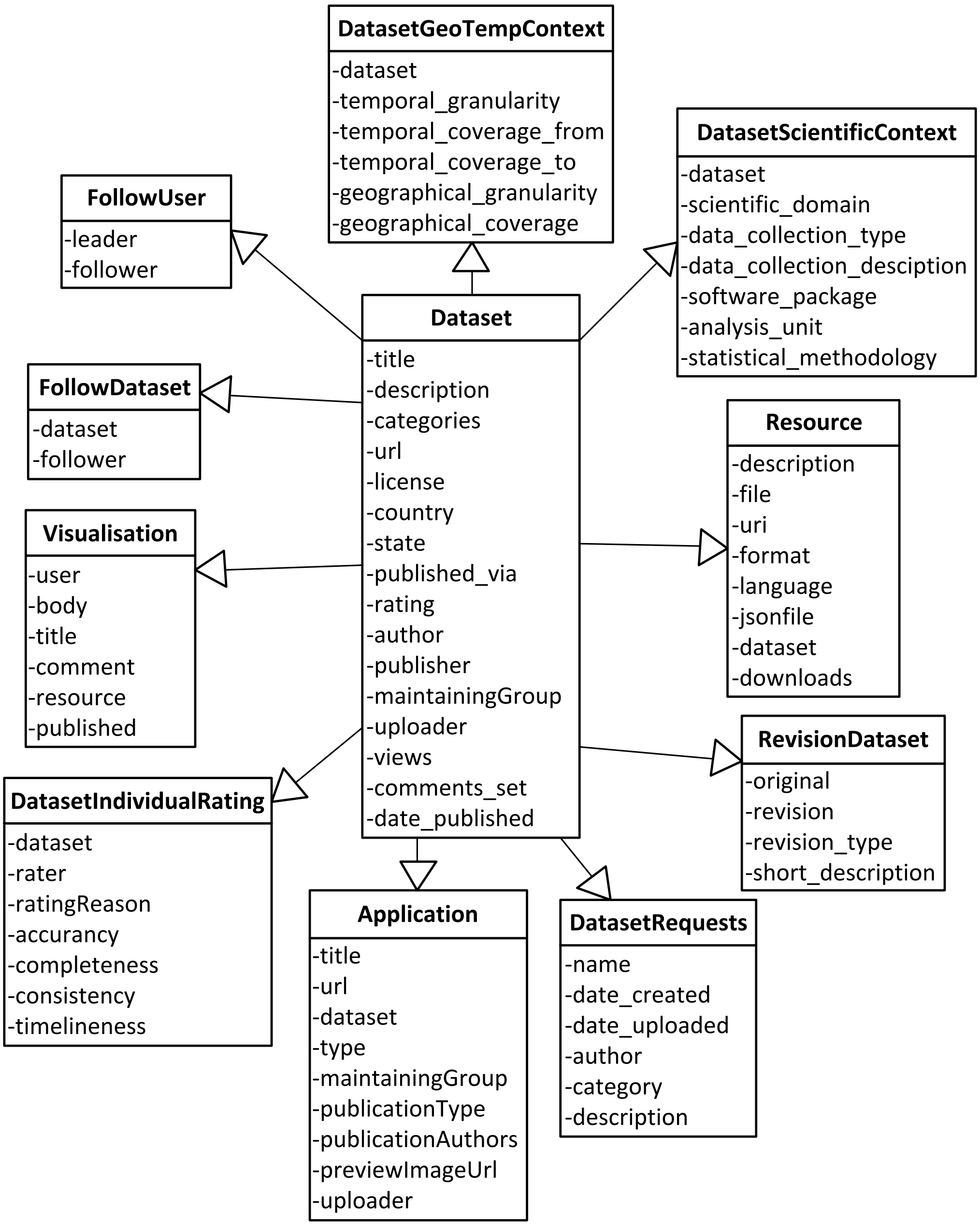

Figure 2: Overview of the metadata fields incorporated in the prototype.

The control OGD infrastructure did not provide interaction mechanisms, and thus it did not facilitate the interaction functionalities that the treatment OGD infrastructure contained. The control OGD infrastructure did provide scores about quality aspects of datasets (e.g. about the completeness of the data and the format that is was provided in) for a number of assessed datasets, in this way also facilitating some data quality functionalities mentioned in section four. At the time of the evaluations, there was no possibility to write a free-text review about the quality of the data or for which purposes it could be used, and this type of functionality was not supported by the control infrastructure.

5.3 Structure of the quasi-experiments

The quasi-experiments were conducted as follows (see Figure 3). First, the quasi-experiment was introduced to the participants and instructions were given. Second, a pre-test (i.e. the first participant survey) was conducted to measure various background characteristics of the participants, as well as their experience with OGD infrastructures. Third, participants completed scenario tasks as well as a second participant survey about the difficulty of these tasks. While the participants completed the scenarios tasks, time measures and observations were used to obtain additional information. Time measures were used to examine how long it took to conduct the scenario tasks and to investigate whether there were significant differences between the time used to conduct the scenarios by the treatment group and the time used by the control group. The results from the observations have already been described by Zuiderwijk and Janssen (2015) and are outside the scope of this paper. Fourth, a post-test was used to measure whether the OGD infrastructure had influenced to which extent the scenario tasks could be completed. Finally, in a plenary discussion the participants were asked which tasks they found most difficult, which tasks they found easiest and whether they had any suggestions to improve the investigated open data infrastructure. More detailed information about the structure of the quasi-experiments is provided in Appendix B.

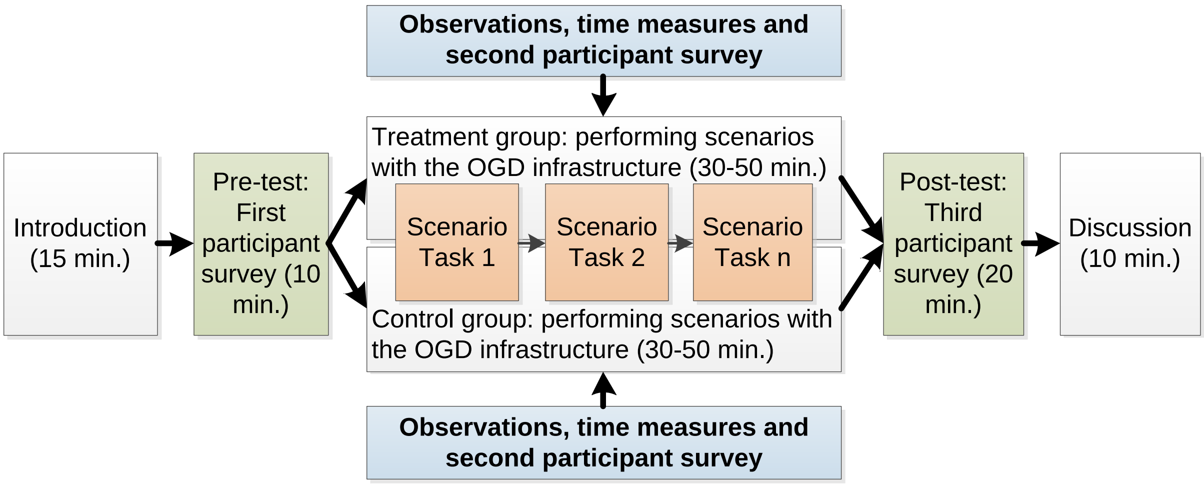

Figure 3: Structure of the quasi-experiments.

6. Findings

In this section we report on and discuss the results from the quasi-experiments. First, the results from the reliability analysis of the constructs will be described, followed by an overview of the characteristics of the participants involved in the quasi-experiments. Subsequently it will be described to which extent the two propositions that were developed in section three were supported by the quasi-experiments.

6.1 Reliability analysis

A reliability analysis was conducted to measure the consistency of the constructs of the model, which was required since the different types of OGD use were measured through a number of statements. Cronbach's Alpha, which is also known as the reliability coefficient, was calculated to obtain information about the reliability of the constructs. Values of 0.7-0.8 are acceptable values for Cronbach's alpha (Field 2005, 668). Murphy and Davidshofer (1988) state that alpha values below 0.6 are unacceptable, values of 0.7 are low, values between 0.8 and 0.9 are moderate to high and values around 0.9 are high. Others (e.g., Davis 1964, Nunnally 1967) have recommended a lower acceptance boundary and believe that Alpha values between 0.5 and 0.6 can still be acceptable. Table 5 shows the Cronbach alpha values for the five constructs (OGD use activities) that are used in our model for both the pre-test and post-test. Except for the open data analysis construct in the pre-test, all Cronbach's Alpha values were moderate (.726) to high (.921). Cronbach's Alpha value for the open data analysis construct in the pre-test is lower (.633), yet not unacceptable.

	Construct	**Number of items**	**Cronbach's Alpha**
Pre-test	Open data searching and finding	4	.772
	Open data analysis	4	.633
	Open data visualisation	3	.817
	Interaction about open data	5	.899
	Open data quality	4	.921
Post-test	Open data searching and finding	4	.855
	Open data analysis	4	.795
	Open data visualisation	3	.726
	Interaction about open data	5	.921
	Open data quality	4	.917

Table 5: Reliability analysis of the constructs included in the pre-test and post-test (N=127, 7=missing).

6.2 Background of the respondents

In total 127 persons participated in the quasi-experiments. Out of the 127 participants, 116 completed the first, second and third participant survey. Eleven persons completed only one or two of these surveys. Table 6 depicts the key characteristics of the participants. The table shows that in both the control and the treatment group of all the three quasi-experiments and the majority of the participants were male. Although no research has been conducted on the gender of the population of OGD users, we expect that the population of OGD users consists of more men than women. For example, research of Seybert (2007, p. 1) found that "many more men than women are employed in computing jobs throughout the EU". The percentage of males per condition (control or treatment) in the quasi-experiments ranged from 65 to 90 per cent and the percentage of females from 10 to 31 per cent. The average age of the 120 participants who provided age information was 27,9 years with a standard deviation of 9,4 (range: 20-65 years old). Participants of the third quasi-experiment were relatively older (μ: 38,7, σ: 12,4, range from 21-65) than participants of the first and second quasi-experiment. Additionally there was a small difference between the average age of participants of the first (μ: 21,8, σ: 1,7, range from 20-26) and second quasi-experiment (μ: 24,4, σ: 2,0 range from 21-32), as participants of the second quasi-experiment were slightly older. The differences in age between the control and treatment groups within the first and second quasi-experiment were relatively small.

		Quasi experiment 1		**Quasi experiment 2**		**Quasi experiment 3**
		Control condition (students)	Treatment condition (students)	Control condition (students)	Treatment condition (students)	Treatment condition (professionals)
Gender	Male	88.9% (8)	90.0% (9)	81.3% (26)	65.0% (26)	61.1% (22)
	Female	11.1% (1)	10.0% (1)	12.5% (4)	30.0% (12)	30.6% (11)
	Missing	0.0% (0)	0.0% (0)	6.3% (2)	5.0% (2)	8.3% (3)
	Total	100% (9)	100% (10)	100% (32)	100% (40)	100% (36)
Age	20-29	100.0% (9)	100.0% (10)	87.5% (28)	95.0% (38)	33.3% (12)
	30 or older	0.0% (0)	0.0% (0)	6.2% (2)	0.0% (0)	58.3% (21)
	Missing	0.0% (0)	0.0% (0)	6.3% (2)	5.0% (2)	8.3% (3)
	Total	100% (9)	100% (10)	100% (32)	100% (40)	100% (36)
Natio-nality	Dutch	100.0% (9)	100.0% (10)	50.0% (16)	42.5% (17)	75.0% (27)
	Other	0.0% (0)	0.0% (0)	50.0% (16)	57.5% (23)	25.0% (9)
	Total	100% (9)	100% (10)	100% (32)	100% (40)	100% (36)

Table 6: Characteristics of the participants of the quasi-experiments.

With regard to nationality it was found that all participants of the first quasi-experiment were Dutch, while in the second and third quasi-experiment more nationalities were represented. In the second quasi-experiment, about half of the participants in the treatment group as well as half of the participants in the control group was Dutch, while the other half consisted of participants from other countries. While the number of foreign participants from the Germanic European cluster were relatively equal in the treatment and control group in the second quasi-experiment, differences between the control and treatment group were visible for the Southern Asian cluster (34,4% in the control group versus 5,0% in the treatment group), the Eastern European cluster (0,0% in the control group versus 15,0% in the treatment group) and the Latin European cluster (3,1% in the control group versus 15,0% in the treatment group). In the third quasi-experiment about 75 per cent of the participants belonged to the Germanic Europe cluster, while most of the other participants belonged to the Anglo cluster (8,3%) or their nationality was not provided (11,1%). The third quasi-experiment only involved one Southern Asian participant. Even though we found that students from the control group were already more positive in the pre-test of the fourth and fifth scenario than the treatment groups of students, and the treatment group of students was already more positive than the treatment group of professionals, nationality does not explain these differences. Moreover, the differences in nationalities appear not to have influenced the results of the pre-test for the first, second and third scenario. We conclude that nationality cannot explain the differences between the three quasi-experiments.

In addition, the participants were asked how often they were involved in open data use in daily life. In all quasi-experiments the minority of people indicated that they had never used open data, varying from 10,0 to 40,6 per cent of the participants within the quasi-experiments. The participants in the control group of the second quasi-experiment seemed to have used open data less often, as more people in this control group had never used open data before compared to the treatment group (40,6 versus 27,5 per cent). Yet, the control group still contained several people who had used open data monthly, weekly and daily. Furthermore, the self-reported level of experience of persons in the control group appeared to be slightly higher than the experience of the participants in the treatment group. Participants who had been involved in open data use were asked to assess their level of experience on a scale from 1 to 10. The average self-reported level of experience varied from 5,8 (control group) and 4,3 (treatment group) in the first quasi-experiment, to 5,1 (control group) and 4,0 (treatment group) in the second quasi-experiment and 6,3 (treatment group) in the third quasi-experiment. Of those participants who had been involved in using open data, most had been involved in using open data for 2 to 5 years (33 participants) or for 5 to 10 years (24 participants). In each quasi-experiment there were participants with different levels of experience.

The number of participants from the first quasi-experiment is too small to statistically analyse the results from this group separately. Since the participants from the first and second quasi-experiment were relatively comparable with regard to gender, age, and experience with open data use, and since both groups contained students from studies in similar directions, the results from the treatment and control groups of the first and second quasi-experiment were combined. We acknowledge that the respondents from these two groups may still be different with regard to certain characteristics that we did not measure. A limitation of this study is that it could not provide insight in this. Although the findings from the control group and treatment group in the first and second quasi-experiment allow for combining them, the findings from the third quasi-experiment will be described separately. This will be done because the differences between age, daily occupation, experience with open data use were larger for this group, which might have influenced the outcomes of the quasi-experiment.

6.3 The ease of OGD use

In this section it is discussed to which extent metadata, interaction mechanisms and data quality indicators influenced the ease of OGD use from the perspective of the participant surveys. Table 7 provides the mean assessment of all the OGD use scenario tasks that were evaluated in the quasi-experiments, as well as the standard deviations. The scenario tasks were rated on a Likert scale from 1 to 7. A mean score of 1 means that respondents strongly disagreed with a statement regarding that scenario, indicating a very negative response. A mean score of 7 means that respondents strongly agreed with a statement regarding the scenario, indicating a very positive response. Mean values around 4 indicate a neutral attitude of the respondent. The means and standard deviations are provided for both the pre-test and the post-test for all the involved control and treatments groups.

At least one of the open data infrastructures that I know enables me to… (pre-test) / The open data infrastructure enabled me to... (post-test)	Means and standard deviations					
	Control group (students, *n=39, 2 missing*)		Treatment group (students, *n=48, 2 missing*)		Treatment group (professionals, *n=33, 3 missing*)	
	Pre-test	Post-test	Pre-test	Post-test	Pre-test	Post-test
Scenario 1: Search for and find open data	μ: 4.89 σ: 0.77	μ: 4.25 σ: 1.37	μ: 4.83 σ: 0.88	μ: 5.45 σ: 0.81	μ: 4.70 σ: 1.16	μ: 4.93 σ: 1.23
Scenario 2: Analyse open data	μ: 4.72 σ: 0.76	μ: 4.14 σ: 1.41	μ: 4.74 σ: 0.86	μ: 5.67 σ: 0.69	μ: 4.48 σ: 1.15	μ: 4.86 σ: 1.06
Scenario 3: Visualise open data	μ: 4.52 σ: 1.16	μ: 3.21 σ: 1.45	μ: 4.50 σ: 1.07	μ: 5.22 σ: 1.19	μ: 4.36 σ: 1.56	μ: 4.43 σ: 1.51
Scenario 4: Interaction about OGD	μ: 4.39 σ: 0.84	μ: 2.16 σ: 1.10	μ: 3.94 σ: 1.22	μ: 4.95 σ: 0.89	μ: 3.22 σ: 1.59	μ: 4.45 σ: 1.42
Scenario 5: Data quality	μ: 4.31 σ: 1.16	μ: 2.45 σ: 1.23	μ: 3.87 σ: 1.29	μ: 5.63 σ: 1.02	μ: 2.90 σ: 1.60	μ: 4.48 σ: 1.85

Table 7: Means and standard deviations of the open data use related scenario tasks on a Likert scale from 1 to 7 (n=127).

When the results of the pre-test for the first three scenarios are compared with the results of the post-test for the first three scenarios, it is observed that the post-test results of the control group are slightly more negative than the pre-test results of the control group. This suggests that the control OGD infrastructure functioned slightly worse than the participants had expected based on their experience with other OGD infrastructures. In contrast, the post-test results of the students treatment group were all more positive than the pre-test results of this group, except for one functionality (i.e. to use various options to search for data, as the participant were already relatively positive about this functionality in the pre-test). For the treatment group of professionals, eight of the eleven post-test results were more positive than the pre-test results of this group. For three functionalities the post-test results were more negative than the pre-test results, namely for 1) drawing conclusions based on the data that they found, 2) visualising data in a chart and 3) visualising data on a map. These functionalities functioned slightly worse than the participants had expected based on their experience with other existing OGD infrastructures. The problems with data visualizations were illustrated by quotes of the participants. For example, professional open data users stated that they: “didn't find the visualization tools easy to use”, “the visualizing (chart, graph, map) was a bit difficult to use”, and “the icons for table, graphs and map in the visualization part seem redundant.” In spite of this, the results from treatments groups are still more positive than the results from the control group.

When we compare the mean values from the pre-test and the post-test for scenarios 4 and 5, it can be concluded that for the control group the post-test values are clearly lower than the pre-test values. For the treatment groups this is the other way around, revealing that the post-test values are all higher than the pre-test values. This suggests that the OGD infrastructure used by the control group performed worse than the participants would have expected based on their previous experiences. The prototype performed better than other OGD infrastructures that the participants had experience with.

To be able to measure whether the level of difficulty of conducting the scenario tasks was significantly different for the control and treatment groups of students, the Mann-Whitney Test (Mann and Whitney 1947) was conducted. The Mann-Whitney test is the non-parametric equivalent of the independent t-test (Field 2009, 540), which was used since the sample did not meet the assumptions for parametric tests (the data was not normally distributed), there was one outcome variable (level of difficulty), the type of outcome was continuous (seven-point Likert scale), there was one categorical predictor variable with two categories (whether the participant was in the treatment or the control group), and different participants were used for the treatment and the control group.

The Mann-Whitney test showed that the level of difficulty of scenario tasks related to all five open data scenarios of the student treatment group differed significantly from the level of difficulty of these tasks of the student control group (see Table 8). On average the students in the treatment group found it significantly easier to conduct scenario tasks related to searching for and finding open data (scenario 1), analysing open data (scenario 2), visualising open data (scenario 3), interacting about open data (scenario 4) and rating and reviewing data quality (scenario 5) than the students in the control group. Since the quasi-experiments only incorporated a treatment group of professional open data users and no control group of professionals, we did not conduct a Mann-Whitney test for the professionals.

	Median of control group (students, n=39, 2 missing)	**Median of treatment group (students, n=48, 2 missing)**	**Mann-Whitney U**
Scenario 1: Search for and find open data	4.50	5.50	1,461.50**
Scenario 2: Analyse open data	4.25	5.75	1,554.00**
Scenario 3: Visualise open data	3.67	5.33	1,612.50**
Scenario 4: Feedback and discussion	2.00	5.00	1,803.50**
Scenario 5: Data quality	2.00	6.00	1,808.50**

* p <.05 ** p <.001

Table 8: Mann-Whitney Test to compare the level of difficulty of scenario tasks of the student treatment group to the level of difficulty of scenario tasks of the student control group (n=91).

The results from the participant surveys indicated that in general the OGD infrastructure improved five types of OGD use: 1) searching for and finding OGD, 2) OGD analysis, 3) OGD visualisation, 4) interaction about OGD and 5) OGD quality analysis. This suggests that metadata, interaction mechanisms and data quality indicators positively influenced the ease of these five types of OGD use.

6.4 The speed of OGD use

In this section it is discussed to which extent metadata, interaction mechanisms and data quality indicators influenced the speed of OGD use. Time duration measures can be used to find out how much attention a person paid to an object (Webb et al. 1973, 134). In this study we assume that the more time is spent on a task, the more attention a person needs to perform the task and the more difficult this task is. Yet is should be realised that other factors may also influence how much time a person spends on a task, such as a person's character and perseverance, and the feeling of pressure from other participants and the facilitator to complete the tasks. It was therefore emphasised in the instructions that time measures were not done to assess the performance of the participants and that they should use as much time as they needed to conduct the tasks.

From the time measures we collected the average number of minutes spent on conducting each of the five scenarios and the standard deviations. Table 9 depicts the results from the time measures for three groups of participants, namely the control group that was present in the first and second quasi-experiment, the treatment group of students that was present in the first and second quasi-experiment, and the treatment group of professionals that was present in the third quasi-experiment. The table shows that participants of the control group needed more time to conduct all the five scenarios than the participants of the student and professional treatment groups. On average the professional open data users in the treatment group conducted the scenarios slightly faster than the students in the treatment group. The participants of the control group needed on average 42 minutes to complete all the five scenarios, while the students of the treatment group needed 29 minutes (31,0% less) and the professionals of the treatment group needed 27 minutes (35,7% less).

Time spent on each of the scenarios	Number of respondents (N), average number of minutes spent (μ) on scenarios and standard deviation (σ)		
	Control group (students)	Treatment group (students)	Treatment group (professionals)
Duration scenario 1 (data searching and finding)	N: 40 μ: 6 minutes σ: 3 minutes	N: 50 μ: 4 minutes σ: 1 minutes	N: 32 μ: 5 minutes σ: 3 minutes
Duration scenario 2 (data analysis)	N: 38 μ: 11 minutes σ: 4 minutes	N: 50 μ: 10 minutes σ: 5 minutes	N: 31 μ: 9 minutes σ: 3 minutes
Duration scenario 3 (data visualisation)	N: 37 μ: 9 minutes σ: 5 minutes	N: 50 μ: 6 minutes σ: 2 minutes	N: 31 μ: 8 minutes σ: 3 minutes
Duration scenario 4 (interaction about data)	N: 37 μ: 9 minutes σ: 4 minutes	N: 49 μ: 5 minutes σ: 2 minutes	N: 27 μ: 5 minutes σ: 3 minutes
Duration scenario 5 (data quality)	N: 36 μ: 4 minutes σ: 2 minutes	N: 47 μ: 3 minutes σ: 1 minutes	N: 24 μ: 2 minutes σ: 0 minutes
Total duration of scenario 1-5	N: 36 μ: 42 minutes σ: 9 minutes	N: 47 μ: 29 minutes σ: 6 minutes	N: 24 μ: 27 minutes σ: 6 minutes

Table 9: Number of respondents, average number of minutes spent on each scenario and standard deviations for the control and treatment condition.

The Mann-Whitney test was used to test whether the average number of minutes spent on the scenarios was significantly different for the control and treatment group. The Mann-Whitney test showed that the number of minutes that the students of the treatment group used to conduct the five open data use scenarios (*Mdn* = 29) differed significantly from the number of minutes that the students of the control group used to conduct these scenarios (*Mdn* = 45), $U = 215.00$, $p < .001$. Moreover, the number of minutes that the professionals of the treatment group used to conduct the five open data use scenarios (*Mdn* = 27) differed significantly from the number of minutes that the students of the control group used to conduct these scenarios (*Mdn* = 45), $U = 81.50$, $p < .001$. This indicates that metadata, interaction mechanisms and data quality indicators allowed for faster use of OGD in the five identified OGD use categories, although the time measures did not focus on each of these three elements but on carrying out the scenario tasks.

6.5 Intermediate variables

Although we found that the developed prototype improves OGD use, we cannot claim that these effects have only been caused by the implemented metadata, interaction mechanisms and data quality indicators. In addition, the participant surveys provided several other intermediate variables which we believe have influenced the performance of the OGD infrastructure. This section discusses intermediate variables.

Table 10 provides the means and standard deviations for six statements regarding intermediate variables concerning characteristics of the facilitator of the quasi-experiment and the quasi-experiment itself. A mean of one indicates that the respondent strongly disagrees with the statement, while a mean of seven points at strong agreement. The table shows that the participants in all three quasi-experiments on average agreed that the practical session on open data use was well-organised and well-structured. The participants of the control and treatment groups disagreed that the facilitator of the quasi-experiment influenced their behaviour and they agreed that the facilitator had a neutral attitude. On average the participants indicated that they were neutral about or slightly agreed with the statement that the scenarios reflected open data use in a realistic way. The participants of the treatment group stated that they learned something by participating in the quasi-experiment, while the control group participants were more neutral about this.

	Control group (students, n=39, 2=missing)	***Treatment group (students, n=48, 2=missing)***	***Treatment group (professionals, n=36, 3=missing)***
The practical session on open data use was well-organized.	μ: 5.08 σ: 1.60	μ: 6.19 σ: 1.02	μ: 5.15 σ: 1.18
The session was well-structured (clear sequence).	μ: 5.51 σ: 1.62	μ: 6.38 σ: 0.67	μ: 5.82 σ: 0.73
The facilitator of this session influenced my behaviour during the session.	μ: 3.21 σ: 1.60	μ: 3.21 σ: 1.88	μ: 2.61 σ: 1.46
The facilitator of this session had a neutral attitude.	μ: 5.74 σ: 1.09	μ: 5.83 σ: 1.12	μ: 5.70 σ: 1.02
The scenarios reflected the use of open data in a realistic way.	μ: 4.51 σ: 1.37	μ: 4.83 σ: 1.48	μ: 4.64 σ: 1.54
I learned something by participating in the session.	μ: 4.31 σ: 1.64	μ: 5.27 σ: 1.33	μ: 5.48 σ: 1.15

Table 10: Means and standard deviations for questions about intermediate variables in the quasi-experiment derived from the participant surveys.

In addition, the participants of the quasi-experiments described several other intermediate variables in the participant surveys. First, the participants of the quasi-experiments pointed at the considerable influence of the user interface. Participants were asked to indicate whether the user interface had influenced their performance, and, if so, whether this influence was positive or negative. In the control group 63 per cent of the participants indicated that the user interface had negatively influenced the difficulty to conduct the scenario tasks, while 20 per cent said that the user interface had a positive influence and 10 per cent said it had not influenced their performance. In contrast, 58 per cent of the participants in the student treatment group and 41 per cent of the participants in the professionals treatment group stated that the user interface of the prototype infrastructure had positively influenced their performance.

Participants in the treatment group mentioned that their performance on the OGD infrastructure was positively influenced through the use of clear and big buttons. For instance, a participant from the treatment group stated that *"using big buttons on places where you expect them […] makes using the infrastructure very user-friendly".* In addition, the clarity of the buttons, headings and logo's, and the organisation of the interface were seen as a success factor of the prototype. Participants stated that that "*the clear buttons, logical symbols and clear setup of the page*" and "*putting the information under clear headings and using logos*" had positively influenced their performance. Another participant pointed at the importance of the contrast and colours, as this person wrote that *"important buttons have a different contrast or colour".* Several participants wrote that the user interface had positively influenced their performance by clearly presenting the possibilities of the infrastructure and the results of data analysis: "*the simple design of the website makes it easier to find data*", the "*clear friendly interface makes users easily find useful information*", the "*clear structure by the different sections makes things easy to find*" and "*it was easy to view the data in an efficient way*".

On the other hand, the user interface had also negatively influenced the performance of participants in the control group. They mentioned that the use of small symbols and the non-intuitive user interface had a negative influence on the way that the control OGD infrastructure could be used. One participant in the control group stated: *"the UI [User Interface] is not intuitive, a lot of tasks couldn't be completed"*, which was confirmed by other participants: *"it's not clear where to click to conduct the tasks", "it was not clear what functions could be used and where data could be found",* "*not a very friendly user interface*", and *"[the control OGD infrastructure] really needs to improve its interface (make it more intuitive)".* Especially the font size seemed to have a negative influence (*"the size of the words was very small. It was not very clear what to do where", "very small symbols", and "the pictograms being very small, it is more difficult to know they are to be used"*).

An additional hindering factor concerned a lack of options to search for and filter data. Participants of the control group said that *"it was not clear […] where data could be found"* and "*too* *much data is 'duttered' and the navigation menu [is] also confusing"*). Regarding difficulties resulting from a lack of experience, participants stated that there was a negative influence from *"having no experience at all with these kind of programs", "having never worked with ENGAGE"* and *"general IT-skills".* Another participant stated: *"this was the first time I looked really into it so it took me some time to search".* Moreover, regarding the number of datasets, it appeared that the number of datasets provided can have a negative influence ("*the index gives too many different datasets to be a good overview*", mentioned by a control group participant, and "*huge number of datasets make search become hard*", mentioned by a treatment group participant). Required registration and problems with signing in on the platform were other hindering factors. The control group participants mentioned, for example: "*registration is always required when you want to analyse something. And you need more than one account*", "*constantly logged out (against will), 'relog' wasn't always possible*" and "*login was not possible, frustration occurred*".

The programmes used appeared to be both hindering and enabling factors, and participants disagreed about this. For instance, a participant of the treatment group stated "*Excel online is a little difficult to use*", while another participant pointed at the positive influence of "*programs that help to visualise the data (Excel)*". Some participants also wrote that "*the programmes are very useful and easy to understand*" and "*easy to use graphs and filters*", whereas someone else stated that "*the way to create a chart was not easy to use*".

It is important to keep the above-mentioned factors in mind when interpreting the results of this study, since these factors appeared to either positively or negatively influence the performance of users of the OGD infrastructures. The influence of the characteristics and behaviour of the respondents was already discussed in section 6.2. The influence of the characteristics and behaviour of the observers and other participants were limited. Two observers of the control group and two observers of the student treatment group wrote that some of the observed participants might have been influenced slightly by the observers, since it was visible to the participants that they were observed. Two observers of the student treatment group stated that some participants may to some extent have influenced other participants, as some asked each other questions, although it was tried to avoid this by separating the participants through partitions between them. The influence of the characteristics and behaviour of the observers and other participants are discussed more in detail by Zuiderwijk and Janssen (2015).

7. Discussion

In this section the contributions of this study are discussed, followed by considerations about the functional infrastructure elements and a number of limitations of this research.

7.1 Contributions of the study

In this study we investigated if the suggested elements of OGD infrastructures improve the ease and speed of use of OGD. Our quasi-experiment results showed that OGD infrastructures that include metadata, interaction mechanisms, and data quality indicators are easier and faster to use than those which do not include these elements. The need to support open data use resounds through the literature, as detailed in section 2.2. We investigated how specific elements of OGD infrastructures can contribute to ease-of-use of OGD and speed of OGD use and thus help fulfil the potential of open data to generate new insights.

In our research we focused on a key aspect of open data progress – efficient use of open data. Data manipulation capabilities and user engagement capabilities of an OGD infrastructure are the two critical indicators for benchmarking OGD status (Sayogo, Pardo, and Cook 2014). Our study posits that data manipulation capabilities can be enhanced by a comprehensive metadata model and the functionalities related to it, such as sorting and filtering, keyword search, language support, metadata overview, viewing datasets online, visualisation tools (in tables, charts, maps). Using open data can often require considerable time and hard work (Braunschweig et al. 2012a); these functionalities can make the task of finding, understanding, analysing, visualising and assessing data less cumbersome and time-consuming. By making data manipulation easier, OGD infrastructures have the potential to diversify the user base of open data and enable a more varied audience to discover and share knowledge derived from open data.

User engagement in open data stands for the ability to interact with the data provider and with other open data users. It offers much potential to move open data forward, as, for example, user-to-provider interaction can help improve the quality of data and make publication more demand-driven; and user-to-user interaction can help attract more users to the portal and enable peer review and collaboration, to name a few benefits. Our study finds that implementing functionalities related to interaction mechanisms in OGD infrastructures improves OGD use. Such functionalities can include social media integration, wikis, discussion forums and comments, or upload of files related to a dataset, as investigated in our quasi-experiments.

Recent research put a spotlight on the second generation of OGD infrastructures, those with advanced data processing and user feedback capabilities (Charalabidis, Loukis, and Alexopoulos 2014). This study used a design science approach to design a novel OGD infrastructure, which is new to the field of open data and which is an example of a second generation infrastructure. The study demonstrated that design science can be used to develop infrastructures which improve OGD use. Thanks to the novel features, OGD infrastructures have the potential to generate a higher level of value and satisfy the objectives of users and providers to a greater extent. Our study contributes in this direction and demonstrates the utility of such elements as metadata, interaction mechanisms, and data quality indicators for moving towards a more advanced OGD infrastructure. We recommend the wider application of design science in the field of open data.

7.2 Considerations regarding metadata, interaction mechanisms and quality indicators

The designed metadata, interaction mechanisms and quality indicators to a large extent rely on sharing findings from OGD use. For instance, connecting a visualisation of a dataset to the data themselves required sharing metadata about the visualisation, and assessing the quality of data requires explaining for what purpose the data were used. This raises the question what incentives open data users have to share this information with other persons. OGD infrastructures should consider this aspect. For instance, OGD users might be more motivated to share findings of OGD use if they will see that this results in improved datasets or if they will be acknowledged for sharing their feedback by giving them credits or so-called kudos that they can earn and exchange for data use service or if they are acknowledged on the home page of the open data platforms or via social media.

Additionally, the value of the metadata, interaction mechanisms and the quality indicators depends on the complexity of the tasks that are conducted and the knowledge of other open data users. Moreover, an OGD infrastructure may be very well-designed with required metadata fields, yet users may not add these required metadata at all. This might explain why some of the metadata aspects and feedback and discussion mechanisms were less appreciated by the participants of the quasi-experiments.

Furthermore, findings from OGD use may be invalid and based on wrongful data use, or wrongful metadata may be added. Sharing and disseminating wrongful findings may not only lead to incorrect interpretations of datasets by other open data users, but this may also be harmful for the provider of the data. For instance, when an open data user presents incorrect data usage and also refers to the original data provider for these results, the data provider may receive criticism as a consequence.

Moreover, data quality assessment is subjective and depends to a large extent on the user's purpose for the data use and the user's frame of reference. Having a larger user base to assess datasets may contribute to reducing this problem, although data quality assessment will always remain subjective. It is therefore important that quality assessment of OGD takes into account different types of data use, different data quality indicators and that users provide a nuanced view on the assessment by describing the context of the way that they used the data. It should be explained for which types of use a certain dataset was useful and for which purposes it was not. These aspects cannot strictly be controlled, although quality checks may already be performed before datasets actually appear online. The maintainer of the dataset may conduct an initial data quality check before the data are published on the platform, which was not the case in our prototype.

Finally, for most functionalities that we tested in the quasi-experiments a critical mass of users is required to make the functionalities successful. For example, discussion messages and data rating reviews cannot be expected to be successful when only a few people provide them. Therefore, open data platforms using metadata, interaction mechanisms and quality indicators require a large user base consisting of both data providers and data users. Engaging users to work with an OGD infrastructure that they are not used to yet is a challenging task.

7.3 Limitations

Although the prototype improved the speed and ease of OGD use, it is important to note that the prototype and this research have several limitations. First, the evaluations focused on a limited number of specific tasks related to metadata, interaction and data quality which needed to be conducted within a limited time frame. Due to time limitations it was not possible to conduct additional tasks or to conduct scenario tasks longer than about 50 minutes. A few participants were not able to complete the scenarios in this time frame. This seemed to be caused mainly by having a problem with one of the tasks, which resulted in spending much time on this particular task. For some functionalities a more thorough evaluation was desired by the participants, which meant that they desired to spend more time on that task. For instance, data quality rating required a thorough analysis of a dataset, and it may be difficult to assess the quality of an open dataset in a short time frame.

Second, in our evaluations we used three types of measures, namely time measures, observations and questionnaires. In addition to these three measures, other measures of the performance of the quasi-experiment participants can be used. For example, when the participants conduct the pre-defined tasks, one may not only investigate the ease and speed of conducting the task, but also the performance of the participant. By using additional measures, more information could be obtained regarding the quality (e.g. the accuracy) of completing the task with the developed infrastructure.

Third, other factors may have influenced the outcomes, such as the user interface, experience with open data use and search options. The participants involved in the quasi-experiments indicated that these factors played an important role in conducting the scenario tasks. The final results and the enhanced speed and ease of use cannot only be attributed to the metadata model, the interaction mechanisms and the data quality indicators.

Fourth, these quasi-experiments involved a number of persons who had limited experience with OGD use (mainly the students). Despite the fact that all students had followed lectures on open data, the majority had not used open data very often themselves. The involvement of professional OGD users partly solved this problem. Yet it was not possible to have a control group of professional open data users, since the number of participants in the treatment group of professionals was too small to divide the group into both a control and treatment group to still be able to conduct statistical tests (which requires at least 30 participants per group). Moreover, in the first and second quasi-experiments the control infrastructure server was temporarily not available for some of the control group participants, so that we could not sufficiently rely on the control OGD infrastructure for the third quasi-experiment. This may have resulted in longer time durations to conduct the tasks for some participants of the control group. Some participants had no problems, while others had to wait for some minutes before they could use the control open data infrastructure again to conduct the tasks. For most participants the server problem occurred when they were conducting the tasks of the third scenario.

Finally, the quasi-experiments pointed at a number of prototype characteristics that can be improved. The prototype requires improvements especially regarding sustainability (*"I need to see* *transparency of the business model that makes engage sustainable over a longer period of time"*, visualisations (*"the visualising (chart, graph, map) was a bit difficult to use"*), the section where participants could post messages to discuss data use (*"having to scroll through all the comments" and "unable to reply to a comment made it a bit frustrating"*), the user interface ("*ENGAGE has high potential but needs some work in terms of interface and what users will need from the platform"* and "s*ome of the interface is intuitive but some things […] made it a bit frustrating"*) and trust generation (there was a lack of information about what ENGAGE does with users' (social media) account information and there were some other concerns about privacy.

8. Conclusions

This study focused on the issue of stimulating OGD use, namely we looked into the elements of OGD infrastructures that can improve OGD use. Based on the literature, we identified five types of activities that OGD use comprises: searching for and finding OGD, OGD analysis, visualizing OGD, interaction about OGD, and OGD quality analysis. In the study we endorsed the idea that three elements of OGD infrastructures – metadata, interaction mechanisms, and data quality indicators – can allow for improving these five OGD use activities. Hence the objective of this study was to use a design science approach to evaluate whether metadata, interaction mechanisms and data quality indicators can improve OGD use. This study focused on the ease and speed of OGD use because we endorsed the idea that ease and speed of OGD use are the most important indicators for successful OGD use. To test the effects of the functional infrastructure elements, we conducted three quasi-experiments with students and professionals, involving 127 participants in total. The participants, divided into treatment and control groups, conducted five scenarios of OGD use using our prototype OGD infrastructure and a control OGD infrastructure. The prototype infrastructure had metadata, interaction mechanisms, and data quality indicators implemented in it. In addition to scenarios, the participants completed pre-test and post-test surveys.

In our quasi-experiments, surveys showed that the treatment group found it significantly easier to conduct scenario tasks than the control group and indicated that the prototype infrastructure functioned better than they had expected based on their experience with other OGD infrastructures. Time measures showed that the treatment group needed significantly less time to conduct all scenarios than the control group. Hence, we conclude that our quasi-experiments indicate that metadata, interaction mechanisms, and data quality indicators positively influence the ease and speed of use of OGD and that OGD infrastructures positively influence the ease and speed of use of OGD. OGD infrastructures in general – and metadata, interaction mechanisms, and data quality indicators in particular – can thus contribute to making OGD use easier and enhance the user experience. To maximise the positive effect of these elements of OGD infrastructures, however, we argue that a critical mass of users is required who can engage in meaningful discussions, provide and peer-review data quality indicators, share and spread the word about open data stories.

The contribution of our study is that we provide solid empirical evidence that, by incorporating three elements in OGD infrastructures, open data use can be stimulated and made easier. Overall OGD use has been lower than expected and little is known about how to stimulate OGD adoption by users; therefore our study is a giveaway lesson for practitioners and data publishers. One contribution to research is that we enhanced the understanding of the use processes of open data, an issue which has received much less attention in open data literature so far than data publication practices. We identified five types of OGD use (searching for and finding OGD, analysing OGD, visualising OGD, interaction about OGD and OGD quality analysis) and discussed intermediate variables which influence them. Future research is recommended to evaluate in more detail how other elements, such as interface design, might influence the ease and speed of use of OGD. We also suggest testing our propositions in larger user groups of professionals, as our study did not involve a control group of professionals. Finally, the application of a design science approach in the field of open data is recommended.

References

Alani, H., W. Hall, K. O'Hara, N. Shadbolt, P. Chandler, and M. Szomszor. 2008. "Building a pragmatic semantic web." *IEEE Intelligent Systems* no. 23 (3):61-68.

Alexopoulos, C., L. Spiliotopoulou, and Y. Charalabidis. 2013. Open data movement in Greece: a case study on open government data sources. In *17th Panhellenic Conference on Informatics*. Thessaloniki, Greece: ACM.

Archer, P., M. Dekkers, S. Goedertier, and N. Loutas. 2015. *Study on Business Models for Linked Open Government Data (BM4LOGD)*. European Commission 2013 [cited February 23 2015]. Available from https://joinup.ec.europa.eu/community/semic/document/study-business-models-linked-open-government-data-bm4logd.

Auer, S., J. Lehmann, A.-C.N. Ngomo, and A. Zaveri. 2013. "Introduction to linked data and its lifecycle on the web." In *Reasoning Web. Semantic Technologies for Intelligent Data Access*, edited by S. Rudolph, G. Gottlob, I. Horrocks and F. van Harmelen, 1-90. Mannheim: Springer.

Behkamal, B., M. Kahani, E. Bagheri, and Z. Jeremic. 2014. "A metrics-driven approach for quality assessment of linked open data." *Journal of Theoretical and Applied Electronic Commerce Research* no. 9 (3):64-79.

Bernstein, L. 1996. "Foreword: importance of software prototyping." *Journal of Systems Integration* no. 6 (1-2):9-14.
Bertot, J.C., P. McDermott, and T. Smith. 2012. Measurement of open government: metrics and process. In *45th Hawaii International Conference on System Sciences*. Hawaii, U.S.A.
Braunschweig, K., J. Eberius, M. Thiele, and W. Lehner. 2012a. OPEN - Enabling non-expert users to extract, integrate, and analyze open data. In *Datenbank-Spektrum. Zeitschrift für Datenbanktechnologien und Information Retrieval*: Springer-Verlag.
Braunschweig, K., J. Eberius, M. Thiele, and W. Lehner. 2012b. The state of open data. Limits of current open data platforms. In *International World Wide Web Conference*. Lyon, France.
Campbell, D.T., and J.C. Stanley. 1969. *Experimental and quasi-experimental designs for research*. Chicago: Rand McNally.
Charalabidis, Y., E. Loukis, and C. Alexopoulos. 2014. Evaluating second generation open government data infrastructures using value models. In *47th Hawaii International Conference on System Sciences* Hawaii, U.S.A.
Charalabidis, Y., E. Ntanos, and F. Lampathaki. 2011. "An architectural framework for open governmental data for researchers and citizens." In *Electronic government and electronic participation joint proceedings of ongoing research and projects of IFIP EGOV and ePart 2011*, edited by M. Janssen, A. Macintosh, J. Scholl, E. Tambouris, M. Wimmer, H. de Bruijn and Y.H. Tan, 77-85. Delft Springer.
Conradie, P., and S. Choenni. 2014. "On the barriers for local government releasing open data." *Government Information Quarterly* no. 31 (supplement 1):S10–S17.
Cronbach, L.J., and P.E. Meehl. 1955. "Construct validity in psychological tests." *Psychological bulletin* no. 52 (4):281.
Davis, F.B. 1964. *Educational measurements and their interpretation*. Belmont: Wadsworth.
Dawes, S. 2010. "Stewardship and usefulness: policy principles for information-based transparency." *Government Information Quarterly* no. 27 (4):377–383.
Dawes, S., and N. Helbig. 2010. Information strategies for open government: challenges and prospects for deriving public value from government transparency. In *9th International Conference on e-Government*. Lausanne, Switzerland: Springer LNCS.
Dawes, S., T. Pardo, and A. Cresswell. 2004. "Designing electronic government information access programs: a holistic approach." *Government Information Quarterly* no. 21 (1):3-23.
De Vocht, L., A. Dimou, J. Breuer, M. Van Compernolle, R. Verborgh, E. Mannens, P. Mechant, and R. Van de Walle. 2014. A visual exploration workflow as enabler for the exploitation of linked open data. In *International Semantic Web Conference*. Trentino, Italy.
Denyer, D., D. Tranfield, and J.E. van Aken. 2008. "Developing design propositions through research synthesis." *Organization Studies* no. 29 (3):393-413.
Detlor, B., M.E. Hupfer, U. Ruhi, and L. Zhao. 2013. "Information quality and community municipal portal use." *Government Information Quarterly* no. 30 (1):23-32.
Dimou, A., L. de Vocht, G. van Grootel, L. van Campe, J. Latour, E. Mannens, P. Mechant, and R. van de Walle. 2014. Visualizing the information of a linked open data enabled research information system. In *Current Research Information Systems Conference*. Rome, Italy: Procedia Computer Science.
Ding, L., V. Peristeras, and M. Hausenblas. 2012. "Linked open government data." *Intelligent Systems, IEEE* no. 27 (3):11-15.
Duval, E., W. Hodgins, S. Sutton, and S.L. Weibel. 2002. "Metadata principles and practicalities." *D-lib magazine* no. 8 (4).
Field, A. 2005. *Discovering Statistics Using SPSS*. London: SAGE Publications.
Field, A. 2009. *Discovering statistics using SPSS*. 3rd ed. London: SAGE.
Foulonneau, M., S. Martin, and S. Turki. 2014. "How open data are turned into services?" In *Exploring services science*, edited by Mehdi Snene and Michel Leonard, 31-39. Geneva: Springer International Publishing.
Garbett, A., C. Linehan, B. Kirman, J. Wardman, and S. Lawson. 2011. Using social media to drive public engagement with open data. In *Digital Engagement*. Newcastle, UK.
Gilb, T. 1997. "Towards the engineering of requirements." *Requirements Engineering* no. 2 (3):165-169.
Hevner, A.R., S.T. March, J. Park, and S. Ram. 2004. "Design science in Information Systems research." *MIS Quarterly* no. 28 (1):75-105.
Ho, J., and R. Tang. 2001. Towards an optimal resolution to information overload: an infomediary approach. In *International ACM SIGGROUP Conference on Supporting Group Work*. Boulder, Colorado, U.S.A.: ACM.

Jeffery, K. 2000. "Metadata: the future of Information Systems." In *Information Systems Engineering: State of the art and research themes*, edited by J. Brinkkemper, E. Lindencrona and A. Sølvberg. London: Springer Verlag.
Jetzek, T. 2015. *The sustainable value of open government data. Uncovering the generative mechanisms of open data through a mixed methods approach*. Copenhagen: Copenhagen Business School.
Jetzek, T., M. Avital, and N. Bjorn-Andersen. 2014. "Data-driven innovation through open government data." *Journal of Theoretical and Applied Electronic Commerce Research* no. 9 (2):100-120.
Joorabchi, A., and A.E. Mahdi. 2011. "An unsupervised approach to automatic classification of scientific literature utilizing bibliographic metadata." *Journal of Information Science* no. 37 (5):499-514.
Jurisch, M.C., M. Kautz, P. Wolf, and H. Krcmar. 2015. An international survey of the factors influencing the intention to use open government. In *48th Hawaii International Conference on System Sciences*. Hawaii, U.S.A.: IEEE Computer Society.
Karr, A.F. 2008. "Citizen access to government statistical information." In *Digital government: E-government research, case studies, and implementation*, edited by H. Chen, L. Brandt, V. Gregg, R. Traunmuller, S. Dawes, E. Hovy, A. Macintosh and C. A. Larson, 503−529. New York: Springer.
Kenny, D.A. 1975. "A quasi-experimental approach to assessing treatment effects in the nonequivalent control group design." *Psychological Bulletin* no. 82 (3):345.
Kuk, G., and T. Davies. 2011. The roles of agency and artifacts in assembling open data complementarities. In *Thirty Second International Conference on Information Systems*. Shanghai, China.
Lindman, J., T. Kinnari, and M. Rossi. 2014. Industrial open data: case studies of early open data entrepreneurs. In *47th Hawaii International Conference on System Sciences*. Hawaii, U.S.A.
Liu, T., F. Bouali, and G. Venturini. 2014. "EXOD: A tool for building and exploring a large graph of open datasets." *Computers & Graphics* no. 39:117-130.
Mann, H.B., and D.R. Whitney. 1947. "On a test of whether one of two random variables is stochastically larger than the other." *Annals of Mathematical Statistics* no. 18:50–60.
March, S.T., and G. Smith. 1995. "Design and natural science research on information technologies." *Decision Support Systems* no. 15 (4):251-266.
Martin, C. 2014. "Barriers to the open government data agenda: taking a multi-level perspective." *Policy & Internet* no. 6 (3):217-240.
Murphy, K.R., and C.O. Davidshofer. 1988. *Psychological testing: principles and applications*. Englewood Cliffs: Prentice-Hall.
Myers, M.D. 2013. *Qualitative research in business and management*. 2nd ed. London: Sage.
Novais, T., J.P.d. Albuquerque, and G.S. Craveiro. 2013. An account of research on open government data (2007-2012): A systematic literature review. In *12th Electronic Government and Electronic Participation Conference*. Koblenz, Germany.
Nunnally, J.C. 1967. *Psychometric theory*. 1st ed. New York: McGraw-Hill.
O'Hara, K. 2012. Data Quality, Government Data and the Open Data Infosphere. In *AISB/IACAP World Congress 2012: Information Quality Symposium*. Birmingham, Great Britain: The Society for the Study of Artificial Intelligence and Simulation of Behaviour.
Oviedo, E., J.N. Mazon, and J.J. Zubcoff. 2013. Towards a Data Quality Model for Open Data Portals. In *XXXIX Latin American Computing Conference*. Club Puerto Azul, Venezuela.
Pearl, J. 2001. Direct and indirect effects. In *17th Conference on Uncertainty in Artificial Intelligence*. Seattle, U.S.A.: Morgan Kaufmann Publishers.
Peffers, K., T. Tunanen, M.A. Rothenberger, and S. Chatterjee. 2008. "A design science research methodology for information systems research." *Journal of Management Information Systems* no. 24 (3):45-77.
Petychakis, M., O. Vasileiou, C. Georgis, S. Mouzakitis, and J. Psarras. 2014. "A state-of-the-art analysis of the current public data landscape from a functional, semantic and technical perspective." *Journal of Theoretical and Applied Electronic Commerce Research* no. 9 (2):34-47.
Potts, C. 1995. Using schematic scenarios to understand user needs. In *1st conference on Designing Interactive Systems: Processes, Practices, Methods, & Techniques*. Ann Arbor, U.S.A.: ACM.
Reichardt, C.S. 1979. "The statistical analysis of data from nonequivalent group designs." In *Quasi-experimentation. Design & analysis issues for field settings*, edited by T.D. Cook and D.T. Campbell. Boston: Houghton Mifflin Company.

Reichman, O.J., M.B. Jones, and M.P. Schildhauer. 2011. "Challenges and opportunities of open data in ecology." *331* no. 11 (Challenges and opportunities of open data in Ecology):703-705
Riley, M.W. 1963. *Sociological research: I. A case approach*. New York: Harcourt, Brace & World.
Salkind, N.J. 2010. *Encyclopedia of research design*. Thoasand Oaks: Sage Publications.
Sayogo, D.S., T.A. Pardo, and M. Cook. 2014. A framework for benchmarking open government data efforts. In *47th Hawaii International Conference on System Sciences*. Hawaii, U.S.A.
Seybert, H. 2013. *Gender Differences in the Use of Computers and the Internet*. European Communities 2007 [cited June 10 2013]. Available from http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-SF-07-119/EN/KS-SF-07-119-EN.PDF.
Shadbolt, N., K. O'Hara, T. Berners-Lee, N. Gibbins, H. Glaser, W. Hall, and M.C. Schraefel. 2012. "Linked open government data: lessons from data.gov.uk." *IEEE Intelligent Systems* no. 27 (3):16-24.
Shadish, W.R., T.D. Cook, and D.T. Campbell. 2002. *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton-Mifflin.
Sieber, R.E., and P.A. Johnson. 2015. "Civic open data at a crossroads: Dominant models and current challenges." *Government Information Quarterly* no. 32 (3):308-315.
Stamati, T., T. Papadopoulos, and D. Anagnostopoulos. 2015. "Social media for openness and accountability in the public sector: Cases in the Greek context." *Government Information Quarterly* no. 32 (1):12–29.
The Data Seal of Approval Board. 2015. *Implementation of the data seal of approval* 2013 [cited April 22 2015]. Available from https://assessment.datasealofapproval.org/assessment_47/seal/html/.
Venkatesh, V., J.Y.L. Thong, F.K.Y. Chan, P.J.-H. Hu, and S.A. Brown. 2011. "Extending the two-stage information systems continuance model: incorporating UTAUT predictors and the role of context." *Information Systems Journal* no. 21 (6):527–555.
Verschuren, P., and R. Hartog. 2005. "Evaluation in design-oriented research." *Quality & Quantity* no. 39 (6):733-762.
Webb, E.J., D.T. Campbell, R.D. Schwartz, and L. Sechrest. 1973. *Unobtrusive measures. Nonreactive research in the social sciences* Chicago: Rand McNally & Company.
Whitmore, A. 2014. "Using open government data to predict war: a case study of data and systems challenges." *Government Information Quarterly* no. 31 (4):622–630.
Yannoukakou, A., and I. Araka. 2014. "Access to government information: right to information and open government data synergy." *Procedia - Social and Behavioral Sciences* no. 147:332-340.
Yin, R.K. 2003. *Case study research. Design and methods*. Thoasand Oaks: SAGE publications.
Zuiderwijk, A. 2015. *Open data infrastructures: The design of an infrastructure to enhance the coordination of open data use*. 's-Hertogenbosch: Uitgeverij BOXPress.
Zuiderwijk, A., and M. Janssen. 2015. Participation and data quality in open data use: open data infrastructures evaluated. In *15th European Conference on eGovernment*. Portsmouth, United Kingdom.

Appendix A: Screenshots of the prototype

Figures 4 to 7 of this appendix provide screenshots of the prototype that was developed as part of the FP7 ENGAGE-project (www.engagedata.eu).

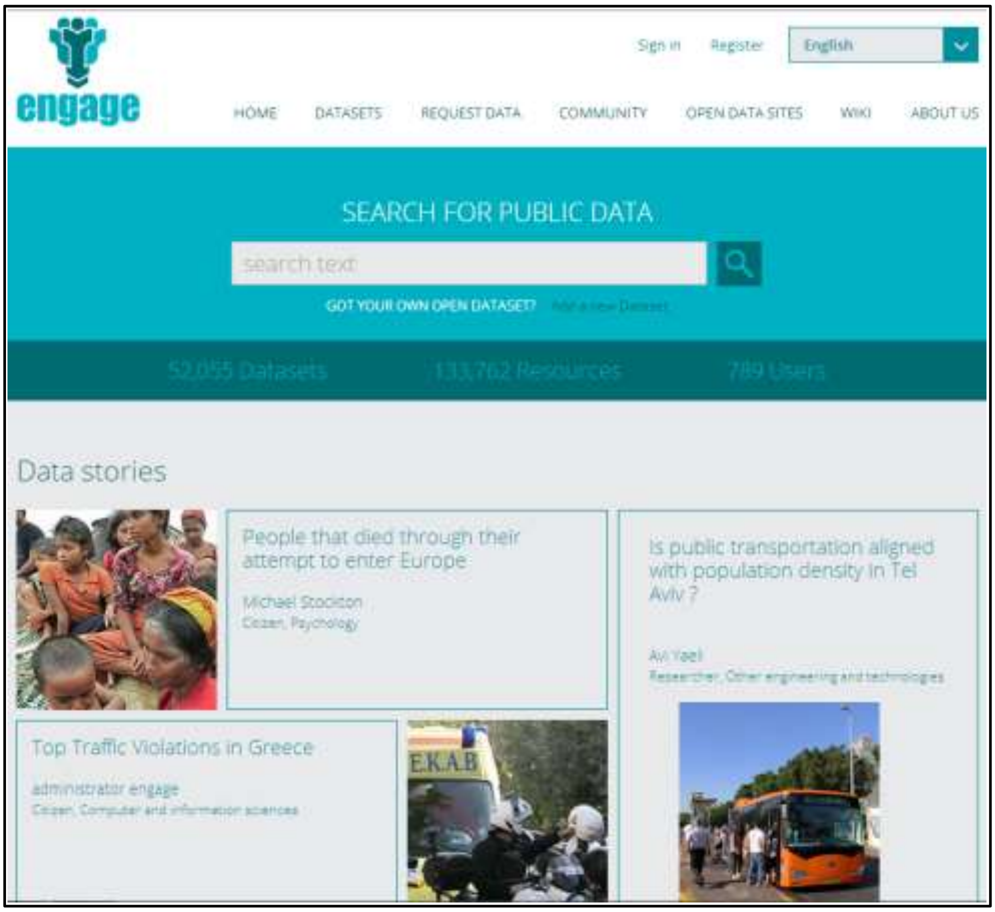

Figure 4: Home page of the prototype.

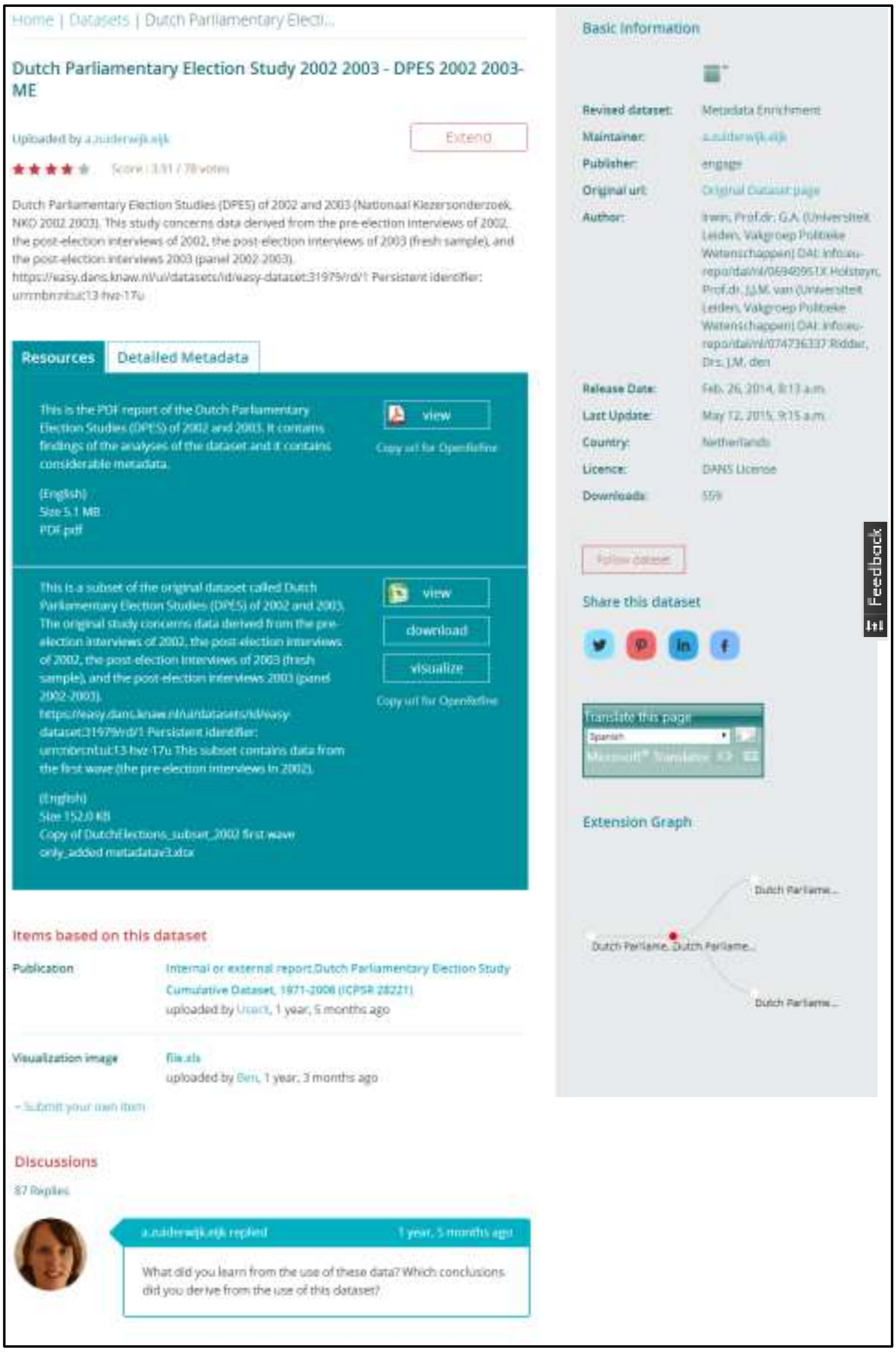

Figure 5: Dataset overview in the prototype.

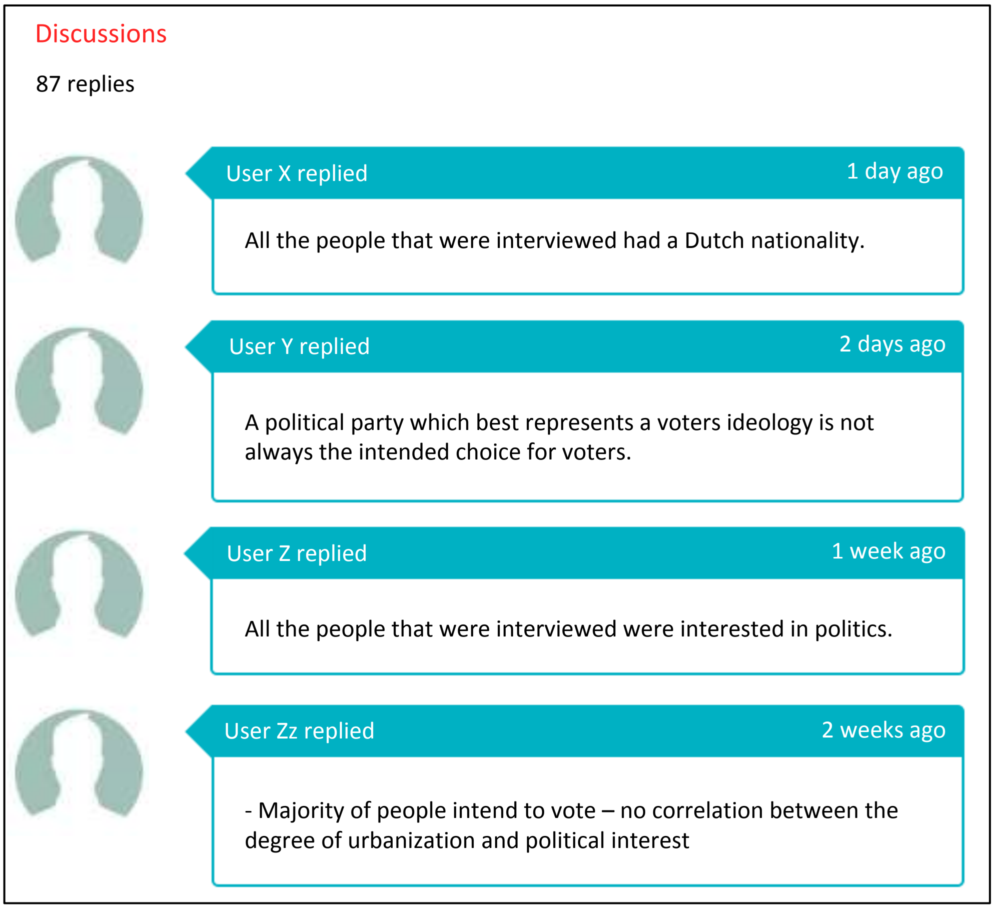

Figure 6: Dataset and data use interaction section in the prototype.

Figure 7: Data quality assessment in the prototype.

Appendix B: Protocol for the quasi-experiments

This appendix provides more information about the conducted quasi-experiments, including information about the introduction, the pre-test, the second participant survey, observations and time measures, the post-test, and the plenary discussion.

1. Introduction

In each evaluation the participants should receive correct and sufficient instructions to participate (Verschuren and Hartog 2005). In the introduction of our quasi-experiments the participants were informed about the objectives of the quasi-experiment and they received instructions. All participants received a participant code, which they needed to provide at the start of the three participant surveys. This allowed for linking the results from the different surveys to one individual participant. The participant code showed to which group the participants belonged (the treatment or control group), what their participation number was (e.g. 1, 2 or 3) and in which quasi-experiment they took part (the first, second or third). The participant code was taped to the tables and visible for the observers, so that they could relate the code to the behaviour of certain participants. In addition, the participants received a hand-out with general instructions, a time plan, links to the participant surveys and an overview of the five main parts of the quasi-experiments, as well as a document with instructions for conducting a number of tasks (referred to as 'scenario tasks'). Participants were ensured that the information that they would provide in the quasi-experiments would be treated confidentially.

2. Pre-test: first participant survey

A pre-test was used to allow for measuring differences between the treatment and control group before the OGD infrastructure was used. The findings from the pre-test were used to identify differences and to compare with the findings from the post-test. The pre-test and post-test were designed in the form of surveys, since this allowed for measuring various constructs before the participants worked with the OGD infrastructure and thereafter, so that the findings from these measures can be compared. This was expected to provide insight in the effects of the OGD infrastructure with the possibility to control for intermediate variables. The first participant survey (the pre-test) was completed online before the participants performed the scenario tasks. The first survey consisted of 19 questions, and most questions were mandatory, i.e. it was not possible to skip these questions. Table 11 shows the questions that were included in the first participant survey.

Part in the first participant survey	Description
1. General questions	12 questions on the demographics of the respondents (e.g. gender, age, daily occupation, experience with data publication and data use)
2. Open data metadata	1 question with several sub questions on the participants' experience with metadata
3. Open data interaction mechanisms and quality indicators	1 question with several sub questions on the participants' experience with interaction mechanisms
4. Expectations of the open data infrastructure	4 questions about the participants' expectations of the open data infrastructure that they would investigate in the scenario tasks
5. Suggestions and comments	1 open question about suggestions and comments

Table 11: Structure of the first participant survey.

3. Second participant survey, observations, and time measures

The following three key measures were used for the quasi-experiments.

1. *Second participant survey*. The second participant survey incorporated various tasks that the participants needed to conduct to operate the prototype. We refer to these tasks as scenarios tasks, since they explored scenarios related to the range of OGD use activities that were identified in section 2.1, including searching for and finding open data, analysing open data, visualising open data, interacting about open data and discussing the quality of open data. Five comprehensive scenarios were developed which comprised eighteen scenario tasks in total. The scenarios were provided to the participants in the form of a survey. This second participant survey included scenario tasks, instructions and questions. The participants were asked to indicate to which extent they found it difficult or easy to conduct the scenario tasks, to rank the tasks based on their ease or difficulty and to indicate whether they were able to complete each individual task. Participants were told that if they could not conduct a certain task, they should just move on to the next task. In that case they were told to write down in the questionnaire that it was 'very difficult' to conduct the task and to state that they were not able to conduct the task. Completing the scenario tasks took the participants between 30 and 50 minutes.

   All participants in both the treatment and the control group used the same dataset to conduct the scenario tasks. This was done to ensure that differences in the results could not be the consequence of differences in the datasets that the participants used. The used dataset concerned Dutch parliamentary elections in 2002 and 2003 (i.e. the Parliamentary Elections Dataset). The DANS infrastructure (see www.dans.knaw.nl/en) was selected for conducting the scenario tasks by the control group. We refer to the DANS infrastructure as 'the control infrastructure'. This infrastructure was selected because it is already used by many Dutch organisations to make their data publicly available, including the Ministry of the Interior and Kingdom Relations, the Ministry of Health, Welfare and Sport, Statistics Netherlands, the Netherlands Organization for Scientific Research, the Research and Documentation Centre and The Netherlands Institute for Social Research. The basic infrastructure is a well-accepted archive for publishing data from social sciences, humanities, behavioural sciences, geospatial sciences and other sciences, and Dutch ministries are nowadays obliged to store their data resulting from policy-oriented research at the basic infrastructure. Furthermore, the control infrastructure did not offer the functionalities that our prototype provided, which made it possible to compare OGD use on the two infrastructures. In addition, the control infrastructure provided English translations of all the functionalities that were required for conducting the quasi-experiments. Since various participants who were involved in the quasi-experiments did not speak Dutch, it was essential that the control infrastructure was available in English.

2. *Time measures*. Time measures were used to examine how long it took to conduct the scenario tasks and to investigate whether there were significant differences between the time used to conduct the scenarios by the treatment group and the time used by the control group. Time duration measures can be used to find out how much attention a person paid to an object (Webb et al. 1973, 134). In this study we assume that the more time is spent on a task, the more attention a person needs to perform the task and the more difficult this task is. Participants registered the time before and after they conducted each of the scenarios.
3. *Observations*. Observations were used to observe whether the behaviour of the participants of the treatment group was different than the behaviour of the participants in the control group. The results from the observations have already been described by Zuiderwijk and Janssen (2015) and are outside the scope of this paper.[1] Observers were responsible for observing a particular group of participants. It was defined in advance which observer should stand where exactly and which participants would be observed. All the observers had experience with

[1] This study of Zuiderwijk and Janssen (2015) showed that interaction mechanisms and quality indicators add value and improve the use of OGD, although this study did not evaluate metadata. According to the observers, participants in the treatment group found it easier to conduct tasks with the prototype related to giving feedback on and discussing open data and rating and reviewing data quality than the participants in the control group.

Information and Communication Technologies. Out of the 18 observations that were conducted for the three quasi-experiments, 12 were conducted by persons who had significant experience with open data. Riley (1963) refers to two types of errors that participant-observation studies can be subject to. First, Riley refers to the ‘control effect’, which is the situation in which the measure process itself becomes an agent working for change and is unsystematic. Second, the biased-viewpoint effect refers to the situation in which the human observer “may selectively expose himself to the data, or selectively perceive them, and, worse yet, shift over time the calibration of his observation measures” (Webb et al. 1973, 114). By using an observation protocol and a semi-structured observer survey we tried to avoid these two types of errors as much as possible. The observers were provided with the protocol, the observer survey and the scenario tasks before the quasi-experiments took place, and they were asked to read these documents carefully before the quasi-experiments. The protocol, the semi-structured observer survey and the scenario tasks were also explained in dedicated training sessions which took place one week before the quasi-experiments took place.

The participants received the scenario tasks and instructions on paper. Each of the six sections in the scenario tasks was displayed on a different page. Moreover, a different colour was used to highlight the tasks for each of these six sections to make clear for the observers on which section people were working. This made it easier for the observers to identify how much time it took for people to work on certain tasks and to indicate to which extent the participants found it difficult or easy to complete these tasks. For instance, yellow highlights on the first page of the scenario tasks indicated that participants were working on the section “searching for and finding open data”.

4. Post-test: third participant survey

A post-test was used to measure whether the OGD infrastructure had influenced to which extent the scenario tasks could be completed. Table 12 shows the questions that were included in the third participant survey. The survey was provided online, and the link to the participant survey could be found in the hand-out that all participants had received at the start of the quasi-experiment. The third participant survey consisted of 26 questions and it took about 15 to 20 minutes to conduct this final participant survey.

Part in the third participant survey	Description
1. Evaluation of the session and the scenarios	1 question with 3 sub questions concerning the quasi-experiment and the scenarios
2. Evaluation of open data metadata	1 question with several sub questions on the assessment of metadata provided by the investigated open data infrastructure
3. Evaluation of open data interaction mechanisms and quality indicators	1 question with several sub questions on the assessment of feedback and discussion mechanisms provided by the investigated open data infrastructure
4. Evaluation of the prototype or control open data infrastructure	22 questions on the assessment of the use of the investigated open data infrastructure
5. Suggestions and comments	1 open question about suggestions and comments

Table 12: The content of the third participant survey.

5. Plenary discussion

Finally, in a plenary discussion the participants were asked which tasks they found most difficult, which tasks they found easiest and whether they had any suggestions to improve the investigated open data infrastructure. The plenary discussions were mainly used to obtain more information about limitations of the study, recommendations for further development of the prototype, and the influence from intermediate variables.