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*Published in:*  
International Journal of Electronic Government Research

*DOI:*  
[10.4018/IJEGR.2018100104](https://doi.org/10.4018/IJEGR.2018100104)

Published: 01/10/2018

*Document Version*  
Publisher's PDF, also known as Version of record


*Please cite the original version:*  
Degbelo, A., Wissing, J., & Kauppinen, T. (2018). A comparison of geovisualizations and data tables for transparency enablement in the open government data landscape. *International Journal of Electronic Government Research*, 14(4), 39-64. <https://doi.org/10.4018/IJEGR.2018100104>

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# A Comparison of Geovisualizations and Data Tables for Transparency Enablement in the Open Government Data Landscape

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## ABSTRACT

Recent years have witnessed progress of public institutions in making their datasets available online, free of charge, for re-use. There have been however limited studies which assess the actual effectiveness of different communication media in making key facts visible to citizens. This article analysed and systematically compared two representations which are relevant in the context of open government data: geovisualizations and data tables. An empirical user study (N=16) revealed that both types of representations have their strengths: geovisualizations make spatial knowledge and the attractiveness of open government data more visible, while data tables are more adequate for the communication of numerical data. The ideas presented are relevant to open data publishers interested in strategies to effectively put the hidden knowledge in current open government datasets into the hands of citizens.

## KEYWORDS

Geovisualization, Open Government Data, Smart Cities, Tabular Data, Transparency

## 1. INTRODUCTION

The topic of smart cities has attracted growing interest from research, industry and local governments. Many definitions exist, reflecting the plurality of perspectives in the context. Within this article, a smart city is defined after Yin et al. (2015) as “a systematic integration of technological infrastructures that relies on advanced data processing, with the goals of making city governance more efficient, citizens happier, businesses more prosperous and the environment more sustainable”. Citizen participation (i.e. getting citizens to timely voice their opinions and wishes) is a key aspect of making city governance more efficient and citizens happier. Indeed, as Milakovich (2010) noted, “Citizen participation provides a source of special insight, information, knowledge, and experience, which contributes to the soundness of government solutions to public problems”. Improved citizen participation, in turn, requires greater transparency as citizens must know (or be made known) what is happening in their city and how they can best contribute to it, in order to effectively participate. As indicated by

DOI: 10.4018/IJEGR.2018100104

previous work (e.g. Janssen, Charalabidis and Zuiderwijk, 2012; Ubaldi, 2013; Hossain, Dwivedi and Rana, 2016), open government data is a key enabler of transparency. There are several dimensions of transparency discussed in (Johannessen and Berntzen, 2018), but in this work the focus is on what Johannessen and Berntzen (2018) called ‘benchmarking transparency’, i.e. the availability of open data (e.g. results from user surveys, demographic information), which citizens and interested parties can use to get a better idea of what is happening within government entities.

Despite a greater availability of open datasets, there is “still a long way to go to put the power of data in the hands of citizens” (The World Wide Web Foundation, 2015). Visualising - or geovisualizing - open data seems the next logical step to put open data in the hands of citizens. Brunetti, Auer and García (2012) and Brunetti et al. (2013) formalised the whole process of getting from a raw dataset to a visualisation as a framework called the Linked Data Visualisation Model (LDVM). LODVisualization (Brunetti, Auer and García, 2012) and LinkedPipes Visualisation (Klímek, Helmich and Nečaský, 2016) are two examples of tools which support LDVM. The current work differs from these two in mainly two ways: (1) a deliberate focus on geographic data preparation, visualisation and interaction (while the two works aforementioned take a more generic approach towards visualisation of open data on the web); and (2) an account for the transformation from non-RDF data sources to RDF (which the two other tools did not intend to address). The main contributions of this article are twofold:

- An empirical investigation of the merits of table-based and geovisualization-based representations for information search in the context of open government data (OGD). Given that geovisualization creation on top of open government data necessitates human effort, empirical investigations of this sort are needed to increase our understanding of when making that extra investment is sensible, and when not;
- An articulation, based on existing theoretical work and data collected from participants, of the distinguishing characteristics of interactive maps and interactive data tables. The value of this characterization lies in a greater understanding of the strengths and limitations of both types of representations when used as communication media.

Background is presented in Section 2, before the introduction of some illustrative geovisualizations developed to increase transparency in the context of OGD (Section 3). Section 4 presents a controlled experiment done with 16 participants to assess the impact of both types of representations on transparency enablement. Section 5 discusses the implications of the results obtained as well as the overall limitations of the work, and Section 6 concludes the article.

## 2. BACKGROUND AND RELATED WORK

Kamaruddin and Md Noor (2017) identified four components of citizen-centricity which are used as a starting point in this paper: openness, transparency, responsiveness and participation. In line with (Michener and Bersch, 2013), transparency is viewed here as having two dimensions: visibility and inferability. The visibility dimension refers to the extent to which information is complete and easily located; the inferability dimension points to the degree to which information can be used to draw accurate conclusions. Conceptually, a map can be viewed as a geometric structure (Peuquet, 1988), a graphical image (Peuquet, 1988) or a set of statements made by an author at a point in time (Degbelo, 2017). Taking the viewpoint of maps as statements as a starting point, web maps are helpful to enable greater transparency in that they can make value more visible and inferable. Value of what? Of activities, processes and products pertaining to the public sphere. Why value? Because getting and keeping citizens interested in the participating in public decisions relies upon an appropriate communication of the value of their participation. Value, as used here, is in line with Benington (2009)’s definition of ‘public value’, and encompasses “ecological, political, social, and cultural

dimensions of value” (or simply said, all that adds value to the public sphere). The remainder of the article will not discuss all possible (and numerous) dimensions of values in the context of public sphere. Instead, it focuses on geovisualizations which enable greater transparency by making the value of open (government) data more visible and inferable. Value of open data has many dimensions (i.e. technical, economic, social, cultural, and political) which were discussed in (Attard, Orlandi and Auer, 2016). The value creation assessment framework of (Attard, Orlandi and Auer, 2016) lists no less than 19 (mostly technical) aspects which should be considered when evaluating the potential of an open government data initiative to enable value creation. Three of these 19 aspects were addressed in the current work (see Section 3):

- **Data usability:** Datasets in formats such as Comma Separated Values (CSV), Portable Document Format (PDF) or Resource Description Framework (RDF) are not necessarily citizen-friendly. Visualising them is a way of adding to their value;
- **Background context:** Linking datasets to related datasets (or simply making more specific their semantics through a conversion into RDF) adds value to existing datasets by reducing ambiguities regarding their interpretation;
- **Rate of reuse:** Providing information about the re-use rate of some datasets is a way of unveiling their actual *social value*.

In sum, transparency is key for increased citizen-centricity on the road towards smarter cities. Geovisualizations of open government data can act as transparency enablers in that they help make the *value* of existing data more visible. The next two subsections briefly review related work on open government data as well as geovisualizations in the context of smart cities. It is worth mentioning here that there is a strong conceptual overlap between city data and open government data. For instance, Ubaldi (2013) defined open government data to include meteorological data, social data (e.g. statistics on employment, health, population, public administration) and transportation data. All these types of datasets *are* also city datasets by virtue of the fact that their geographical component is tied to (one or many) cities. Put differently, georeferenced open government data is very likely city data.

## 2.1. Open Government Data

Open Government and Open Government Data have attracted significant attention from research in the recent years. Criado, Ruvalcaba-Gómez and Valenzuela-Mendoza (2018) found transparency and participation to be strongly tied to open government in their review of an international literature covering the period of 2011-2015. Other reviews of the literature have pointed out that OGD includes a wide range of topics, both technological and non-technological ones (Charalabidis, Alexopoulos and Loukis, 2016), that most common approaches to OGD currently include data portals, data catalogues, and services (Attard *et al.*, 2015), and that potential users of open government data include developers, activists, non-governmental organizations and citizens (Safarov, Meijer and Grimmelikhuisen, 2017). Factors influencing citizens’ participation in open government projects include the perceived enjoyment of the project, the extent to which they believe they can actually change their environment, and their attitude towards civic duties (see Wijnhoven, Ehrenhard and Kuhn, 2015).

Jetzek, Avital and Bjørn-Andersen (2013) pointed out that OGD has the potential to increase social welfare through the generation of economic and social value. Along the same lines, Geiger and von Lucke (2012) indicated that OGD comes with several opportunities such as the modernizing of public administrations in an increasingly open world, the strengthening of an active citizenship, and innovations for citizens and public administrations. Despite these promises, a number of studies (e.g. Zuiderwijk *et al.*, 2012; Beno *et al.*, 2017; Benitez-Paez *et al.*, 2018) have indicated some obstacles on the roads towards reaping these benefits. Solutions to facilitate OGD re-use include frameworks, ontologies as well as tools. Benitez-Paez, Comber, *et al.* (2018) proposed a framework to improve re-use of open geodata in cities. The framework included four components: user-focused

metadata, community of re-use, data users' identification, as well as re-use focused legal terms. Another framework proposed in previous work is the 'Linked Government Data publishing pipeline' (Maali, Cyganiak and Peristeras, 2012), which is based on Google Refine, and aims at enabling data consumers to convert government data of their choice into linked data. With respect to ontologies, Muñoz-Soro et al. (2016) developed PPROC, an ontology to support the semantic description of public procurement processes and contracts. Mockus and Palmirani (2017) presented the OGDLM ontology, a collection of terms for the description of legal rules, copyright and database rights in the context of OGD. Regarding tools, Futia et al. (2017) presented a linked data driven approach (as well as a system) to integrate Italian procurement datasets and enhance information coherence in open Italian public procurement datasets. Matheus, Janssen and Maheshwari (2018) argued that dashboards can improve transparency and accountability, and presented two dashboards re-using open government datasets from the city of Rio de Janeiro, Brazil. Degbelo et al. (2019) presented the OCT Transparency Tool, a prototype which aims at increasing transparency by informing about open dataset usage in applications, places from which an app has accessed datasets, and places from which datasets were called. The IES CITIES platform (López-de-Ipiña et al., 2013; Aguilera et al., 2017) takes advantage of existing open government data and combines it with urban data generated by sensors as well as user-generated data, to offer a variety of services pertinent to urban life.

## 2.2. Geovisualizations for Open Government Data and Smarter Cities

A geovisualization can be defined as the 'mapping of geographic information to visuals' (definition adapted from Murray, 2013). In line with (Roberts, 2008), geovisualizations can be of one of seven types: Maps/Cartograms, Networks, Charts/Graphs, Tables, Symbols, Diagrams and Pictures. That is, any map is a geovisualization, but a geovisualization need not be a map. Geovisualization is a form of information processing, a compelling form of rhetorical communication, and is more a process of creating than a process of revealing spatial knowledge (see Dodge, Mcderby and Turner, 2008).

The importance of geovisualizations for the realization of the vision of smarter cities has been acknowledged in previous work. As Dykes et al. (2010) indicated, the quantity, complexity and heterogeneity of the city datasets pose a series of research challenges, and geovisualizations can play a vital role in making sense of these datasets. Degbelo, Granell, et al. (2016) listed six citizen-centric challenges for smart cities (i.e. engagement of citizens, the improvement of citizens' data literacy, the pairing of quantitative and qualitative data, the need for open standards, the development of personal services, and the development of persuasive interfaces), and pointed out that maps are a helpful tool in addressing all six challenges. Fechner and Kray (2014) and Marzouki et al. (2017) argued that geovisualizations can facilitate citizen engagement. In particular, Fechner and Kray (2014) proposed that maps can be useful in public online dialog platforms, and presented 'Dialog Map', an interactive map which displays engagement opportunities for sustainability projects and open issues. If the conjectures on geovisualizations and citizen engagement in the literature paint a positive future, one must not forget that involving citizens comes with its' own bunch of issues. For instance, Ballatore (2014) listed a number of issues in collaboratively-generated digital cartographic artefacts (e.g. intentional or unintentional defacement), and these issues are likely to resurface, should geovisualizations be adopted as medium during participatory processes in cities.

Geovisualizations have been used as a tool to support the analysis of criminal activity (Roth, Ross and MacEachren, 2015; Godwin and Stasko, 2017), urban changes over a period of 250 years (Tucci, Giordano and Ronza, 2010), public health (Robinson, Roth and MacEachren, 2011) and urban emissions (Ahlers *et al.*, 2018), to name but a few. Recent work has also begun to explore the use of social-media generated datasets for a greater understanding of city processes. Godwin, Wang and Stasko (2017) used geotagged tweets to construct representations of neighbourhood topics as typographic maps. Robinson (2018) presented a framework to evaluate the design of maps that reach rapid popularity via social media dissemination. Graves and Hendler (2013, 2014) provided insights into users' wishes in the context of visualization of open government data. They reported for instance

that users find it important to (1) know where the data used in a visualization comes from, (2) know how the data was processed to yield a visualization, and (3) be given the possibility of modifying existing visualizations a bit, and (4) bring in their own data, and have a visualization which they have seen on the Web be re-created for them.

Collections of (geo) visualizations for city data on the Web have begun to emerge. Examples include DataMade (<https://datamade.us/>), CityViz (<https://cityfutures.be.unsw.edu.au/cityviz/>), Visualizing Cities (<https://cityvis.io/>), CityLab (<https://www.citylab.com/>) and Data-Smart City Solutions (<https://datasmart.ash.harvard.edu/>)<sup>1</sup>. A drawback of number of these geovisualizations is that re-using them in different contexts is still a challenge. Degbelo and Kray (2018) suggested that increasing the intelligence of these geovisualizations could help mitigate that issue.

### 2.3. Summary

This brief summary of previous work illustrates that transparency is an important topic for OGD, and that solutions are coming forth to help mitigate open data re-use issues. Geovisualizations are crucial for OGD. Their importance has been recognized for the broader vision of smarter cities, and they are key too for OGD, since georeferenced OGD is city data. Despite the use of geovisualizations in several smart cities use cases, there is still a need for empirical investigations clarifying the actual role of geovisualizations in enabling (or not) transparency, a topic of importance for both OGD and smart cities visions. This gap is addressed in the remainder of the paper (see Section 4).

## 3. EXAMPLE WEB MAPS ENABLING GREATER TRANSPARENCY

As discussed in (Degbelo, 2017), two techniques are particularly suitable to enable greater transparency in the context of open government, namely Linked Data and visualisation. Linked Data increases transparency for machines, and visualisations do so for humans. To illustrate the idea, 36 students (divided into groups of three to six members) were asked to take existing open data, transform it into linked open data, and geovisualise it. The students were part of two classes organized at two consequent years (one class took place with 19 people in the winter term 2015/2017, and the second took place with 17 people in the winter term 2016/2017).

We designed both classes around the idea of blended learning, thus combining activities online with those at the classroom. We shared readings and visualization examples online. This was done in a flipped (or inverted) classroom fashion (see e.g. Mason, Shuman, and Cook 2013). Each group also presented their progress in online sessions aired between University of Münster and Aalto University (in Finland). We used classroom sessions for agile co-creation of sketches of data models and visualizations by groups. Different phases of the works by students were presented via gallery walk for getting feedback from other groups, and to support improving their own work. For class designs, we prioritized active learning methods over passive learning ones for both online and classroom.

In the first class, open data from Münster was used as raw data; in the second class, participants were asked to work with open data of their choice. They were all non-familiar with Linked Data, and had various degrees of familiarity with web technologies (like HTML5, CSS, JavaScript or Node.js). The apps based on existing open data, and built as part of the practical work within the classes are: Crime Mapper (A1): a web app for citizens and tourists to get a better overview of the crimes in Greater London; Münster Households (A2): an interactive map for citizens and city councils to see households data from Münster between 2010 and 2014; Münster Migration (A3): an interactive map for citizens and city councils to go through migration statistics from Münster between 2010 and 2014; Münster Population (A4): an interactive map for citizens and city councils to browse population data from Münster between 2010 and 2014; Münster Social Insurance (A5): an interactive map for citizens and city councils to get an idea about the number of employees subject to social insurance contributions in Münster between 2010 and 2014; Münster Unemployment (A6): an interactive map for citizens and city councils

to explore unemployment data from Münster between 2010 and 2014; Referendum Map Münster (A7): an interactive map for citizens and city councils to see results of the 2016 referendum regarding opening shops in the Münster city centre; and Wildlife Columbia (A8): a web app for policy makers and researchers to see information about protected natural reserves in Columbia, and species that inhabit these reserves.

Besides increasing data usability and providing background context about the datasets intrinsically, a novel feature of the web maps is the provision of information of the rate of open data usage. Technically, all web maps use the semantic API from (Degbelo, Trilles, et al., 2016) which enables app and dataset usage tracking, resulting in greater transparency. Degbelo, Trilles, et al. (2016) suggested that APIs which return data items according to their types - what they called semantic APIs - would lead to greater transparency (for developers) in an open government context, and identified recurrent categories of open datasets based on a survey of 40 European open data catalogues. Each of the web maps using the semantic API gets a 'transparency badge' (see Figure 1, bottom left corner), which indicates their support for dataset usage tracking. By clicking on this badge, the user is redirected to a dashboard-like platform which provides information about all applications available, the open datasets needed for their functioning, and their access rates of these datasets (see Figure 2). The information potential of users regarding what is happening with open datasets (i.e. how these are used in one or many apps) is thereby increased. One can also visualise most demanded datasets using the 'Datasets' tab (see Figure 2).

The transparency badge is mainly useful here to inform about rate of dataset usage. Yet, its conceptual scope should not be limited to this. One could envision further useful information provided to citizens after a click on a transparency badge. Example of relevant information in the context of open data visualisation include (the list is far from exhaustive):

**Figure 1. Münster unemployment - Application with visualises open data from Münster as a web map. The transparency badge signals greater transparency support (i.e. the presence of extra, useful contextual information) for users of the visualisation.**

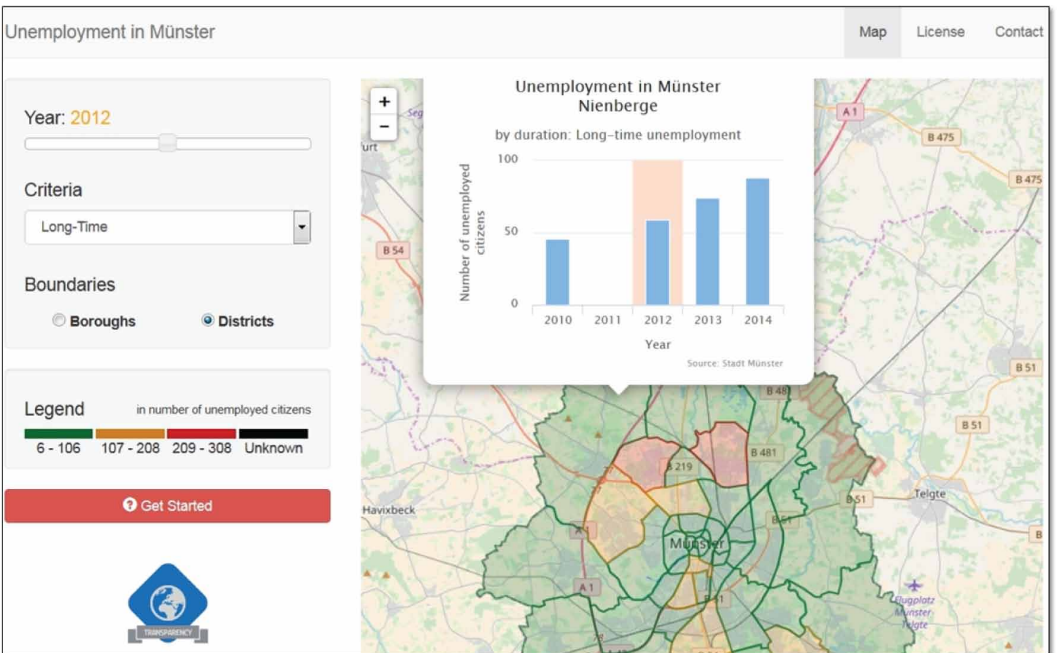


Figure 2. Dashboard-like visualisation of available applications as well as their access rates to existing applications

Apps	Categories	Datasets	Usage	Start Tour	Register
More	Name	Description	Category Search	Dataset Search	App Type
	Münster Migration	Visualization of migration statistics from Münster	1	18	WebApp
	Münster Households	Map of households data from Münster	2	163	WebApp
	Crime Mapper	Mapping crimes of Greater London	1	48	WebApp
	Münster SocialInsurance	Employees subject to social insurance contributions in Münster	2	26	WebApp
	Münster Population	Map of population data from Münster	1	57	WebApp
	Wildlife Columbia	Mapping natural reserves in Columbia	1	37	WebApp
	Referendum Map Münster	Mapping referendum data from Münster	1	152	WebApp
	Münster Unemployment	Visualization of unemployment data from Münster	1	39	WebApp

- **Estimated interaction time to get most out of the visualization:** This estimate could be provided by the creator of the visualization and her experience using it, or computed based on feedback provided by past users of the visualization;
- **Source datasets of the visualisation:** According to the survey from (Graves and Hendler, 2013, 2014), this is a most desired information by participants;
- **Trustworthiness of the visualisation, and of the dataset:** As Tim Berners Lee recently reminded, “It’s too easy for misinformation to spread on the web” (Berners-Lee, 2017). The transparency badge could, for example, say whether the data (and/or its visualisation) has been verified by a public institution;
- **Hints about data completeness:** Participants from (Beno et al., 2017) mentioned data incompleteness as one of the most severe barriers to open data adoption. Informing about data completeness may not solve the issue, but is already a way forward;
- **Hints about data currency:** The lack of updates of published open data appears at the top of the list of participants from (Benitez-Paez, Degbelo, et al., 2018) when it comes to major barriers to open data re-use. Here also, informing about data updating policies does not solve the issue, but can, at least, help citizens know what to expect;
- **Licensing information about the dataset, and the visualisation:** This is mostly relevant to developers interested in re-use;
- **Purpose of the data and the visualisation:** Why the dataset has been collected, and why the visualisation has been created;
- **Adoption examples:** How the dataset has been adopted elsewhere, and how it has been used in that (or these) scenario.



The final list of the transparency badge's informational items may be decided by its provider. This being said, experience from the food industry (where nutrition facts labels for packaged foods have proven simple and informative to consumers) suggests that standardisation of the informational items of a transparency badge (e.g. through the W3C) could be helpful for the web as a whole at some point.

The detailed analysis of the web maps using the taxonomy of interaction primitives from (Roth, 2013a) and current visual variables (Roth, 2017) was presented in (Degbelo and Kauppinen, 2018). Table 1 summarizes the results. As Griffin (2017) indicated, the use of 'colour saturation' as visual variable in its own right is uncommon. In addition, assessing 'colour saturation' with the human eye is error-prone. Thus, 'colour saturation' was not included in the analysis. The visual variable of 'location' is present in all visualizations, and therefore not mentioned in the table. Finally, the analysis took only the map component of the geovisualizations into account (i.e. other components such as histograms, when present, were not included).

**Table 1. Features of the web maps from (Degbelo and Kauppinen, 2018) - NT: Number of triples; NV: Number of vocabularies used; CV: custom vocabulary**

	NT	NV (CV)	Open Dataset Used	Visual Variables	Operands // Objectives Supported	Work Operators
A1	485,331	10 (1)	crime data	colour hue	space-alone, attributes-in-space, space-in-time // identify	pan, zoom, retrieve, resymbolize, overlay, calculate
A2	31,162	21 (1)	households count data	colour hue, colour value	space-alone, attributes-in-space, space-in-time // identify	pan, zoom, retrieve
A3	1,391	4 (1)	migration data	-	space-alone, attributes-in-space, space-in-time // identify	pan, zoom, retrieve, resymbolize, overlay
A4	6,668	9 (1)	population data	colour hue, colour value	space-alone, attributes-in-space, space-in-time // identify, compare	pan, zoom, retrieve, resymbolize, overlay, calculate
A5	1,869	8 (1)	social insurance contribution data	colour value	space-alone, attributes-in-space, space-in-time // identify, compare	pan, zoom, retrieve, calculate
A6	4,399	6 (1)	unemployment data	colour hue	space-alone, attributes-in-space, space-in-time // identify	pan, zoom, retrieve, overlay
A7	1,327	5 (1)	election data	colour hue	space-alone, attributes-in-space // identify	pan, zoom, retrieve, overlay
A8	2,432	16 (1)	endangered species data, deforestation data, social index data	colour hue	space-alone, attributes-in-space // identify	pan, zoom, retrieve, resymbolize, overlay, search

## 4. COMPARING GEOVISUALIZATIONS AND DATA TABLES FOR THE PURPOSE OF TRANSPARENCY ENABLEMENT

Given the web maps generated in the previous section, the question is whether they truly enable transparency as advanced by previous work (e.g. Degbelo, 2017). A controlled experiment was performed to collect some empirical evidence for this question. The experiment used the geovisualizations A4 and A6 from Table 1 and their respective table-based data sources from the city council of Münster<sup>2</sup>. The study has simulated information search by citizens in the context of open government, and rested on the following key assumptions:

- A table-based rendering of some data, and a geovisualization-based rendering of the same data are, in fact, two representations of the same data. Representation is used here in the sense of (Mocnik and Fairbairn, 2018): ‘Representations are substitutes for, and transformations of, reality and real-world phenomena: they are layers between our understanding and the real world, intended to be used as surrogates for experiencing the real world’;
- A source dataset and its geovisualization can be considered informationally equivalent in the sense of (Larkin and Simon, 1987): ‘Two representations are informationally equivalent if all of the information in the one is also inferable from the other, and vice versa’;
- A representation A is said to enable greater transparency than another representation B, if and only if A provides faster access to some information than B;
- ‘Information is the reply to a question’ (Bertin, 1981, page 11).

### 4.1. The Spirits of Map-Based and Table-Based Representations

A spirit of a representation is “the important set of ideas and inspirations that lie behind (and, significantly, are often less obvious than) the concrete machinery used to implement the representation” (Davis, Shrobe and Szolovits, 1993). Table 2 presents an overview of most important underlying assumptions of geovisualization-based and table-based representations. The ideas presented in Table 2 are adapted from Mocnik and Fairbairn (2018), who provided a detailed comparison of map-based and text-based representations for the purpose of storytelling. It is worth mentioning here that ‘table-based representation’ denotes the presentation of a dataset presented in the form of a table in a PDF file (as is often the case of open data in the context of open government). Aspects touched upon in Table 2 address characteristics of geovisualizations and tables when they play (Davis, Shrobe and Szolovits, 1993)’s fifth role of knowledge representations, that is, when they are used as media of human expression and communication. Since the experiment described later primarily focused on the map component of the geovisualizations, the brief comparison that follows only exposes the core similarities and differences between data tables and maps:

**Table 2. Similarities and differences between maps and data tables when used as media of human expression and communication**

Aspect	Map-Based Representation	Table-Based Representation
Nature	Spatially ordered network	Matrix
Number of dimensions	Two-dimensional	Two-dimensional
Interactivity	Low to High	Low
Dependency	Dependent on a data table	Standalone
Level of geographic detail	Restricted	Boundless
Modelling of spatial relations	Spatial relations implicitly represented; incoherencies hardly possible	Spatial relations need to be explicitly represented; incoherencies possible

- **Nature:** Following (Bertin, 1981; Ermilov, Auer and Stadler, 2013), a table is a matrix, where data items are ordered according to some characteristics; a map on the contrary is a spatially ordered network (see Bertin, 1981, 1983). The nodes of this network are points, and the edges are connecting lines between two points;
- **Number of dimensions:** It follows from their nature that both tables and maps have two dimensions. Since the context here is that of digital representations, these two dimensions are those of the screen;
- **Interactivity:** Both types of representations are interactive, albeit with some noticeable differences. Interactive maps, which are most common in the digital age, are a ‘dialogue between a human and a map mediated through a computing device’ (Roth, 2013b). Data tables in a PDF file are primarily static, but afford interactivity through the use of the search function. Interactivity in the context of PDF data tables will arguably remain low; in contrast, interactive maps support a range of interaction possibilities from ‘low’ to ‘high’ as the cartography cube (see for example Roth, 2013b) suggests;
- **Dependencies:** As mentioned in (Bertin, 1981), ‘any graphic construction originates with a data table’. That is, a map is necessarily dependent on another type of representation, namely the one from which it derives; a data table, on the contrary, can stand on its own. Thus, a data table is a standalone representation, while the map is a dependent representation;
- **Level of geographic detail:** As discussed in (Mocnik and Fairbairn, 2018), geographic details cannot be added to maps *ad infinitum*. A map usually has a fixed number of predefined levels of details (e.g. a fixed number of zoom levels), but this is typically not the case for data tables, where the use of text enables boundless levels of geographic details (at least in theory);
- **Modelling of spatial relations:** A map shows relative locations, spatial hierarchies, spatial patterns and spatial arrangements, representing thereby spatial relations implicitly (Mocnik and Fairbairn, 2018). Since these spatial relationships are exactly similar to spatial relationships between objects in the real world, spatial incoherencies are hardly possible. Data-tables cannot implicitly impose spatial relations (these can then be inferred through a closer scrutiny of the table), and this implies that spatial incoherencies/contradictions are possible.

## 4.2. User Study

The main research question examined during the study is ‘what are differences, if any, between geovisualization-based and table-based representation for transparency enablement in the OGD context’? Data to answer the question was gathered during a user study, in which participants were asked to complete a set of information search tasks (see Table 3):

- **Tasks:** The six information search tasks were defined based on previous work (Roth, 2013a; Roth and MacEachren, 2016). Roth (2013a) presented an empirically derived taxonomy of interaction primitives. The primitives were arranged across the dimensions of operand (physical/virtual object with which the user interacts), goal (ill-defined task motivating the use of a visualization), objective (well-defined task supporting the goal), and operator (action supporting the goal). Roth identified five primitive objectives (identify, compare, rank, associate and delineate) and three primitive operands (space-alone, attributes-in-space, space-in-time), and used objective-operand pairings to define and test benchmark tasks for geovisual analytics in (Roth and MacEachren, 2016). To minimize the effect of participants’ fatigue, the focus was only on the ‘identify’ and ‘compare’ objective primitives in this study. Definitions of both objective and operands for the study, adapted from (Roth, 2013a), are:
  - **Identify objective:** Examine an individual data element;
  - **Compare objective:** Determine the similarity and difference between two data elements;

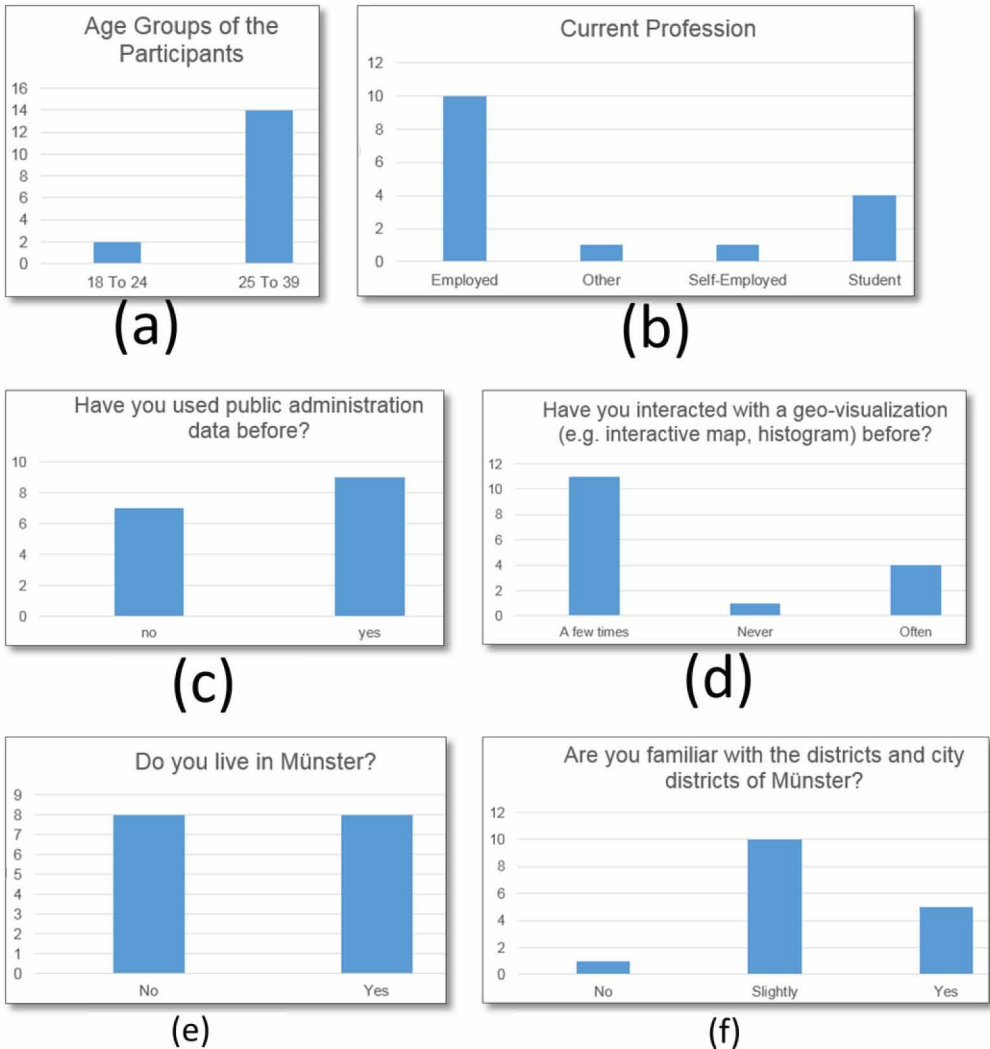
Table 3. Information search tasks given to the participants during the study

Dataset	Objective	Information Search Questions		
		Space-Alone	Attribute-in-Space	Space-in-Time
Population	<i>Identify</i>	In which district is the city district of 'Berg Fidel' located? [T1]	How many people live in the city district of 'Berg Fidel'? [T2]	What was the population of the city district of 'Berg Fidel' in 2013? [T3]
	<i>Compare</i>	Among 'Sentrup', 'Aaseestadt' and 'Geist' which one is the northernmost city district? [T4]	Among 'Nord' and 'West' which district has the larger population? [T5]	Has the population in 'Mitte' increased between 2013 and 2014? [T6]
Employment	<i>Identify</i>	In which district is the city district of 'Herz-Jesu' located? [T1]	How many employees are in the city district of 'Herz-Jesu'? [T2]	How many employees of the city district of 'Herz-Jesu' were in 2013? [T3]
	<i>Compare</i>	Among 'Handorf', 'Geist' and 'Rumphorst' which one is the northernmost city district? [T4]	Among 'Südost' and 'Hiltrup' which district has the most employees? [T5]	Has the number of employees in 'Mitte' increased between 2013 and 2014? [T6]

- **Space-alone operand:** Interactions with the geographic component of the visualization only;
- **Attributes-in-space operand:** Interactions with the mapped attributes to understand how characteristics or qualities of geographic phenomena vary in space;
- **Space-in-time operand:** Interactions with the temporal component of the map to understand how geographic phenomena change over time;
- **Procedure:** A within-group design, where participants were exposed to both representations was used. To minimize learning effects, the order of exposure to the representations was counterbalanced, and the participants were randomly assigned to one of four groups: Group1 (A4, D6), Group2 (A6, D4), Group3 (D4, A6) and Group4 (D6, A4). First, participants were welcomed and provided general background information about themselves using a background questionnaire. Second, they performed the six information search tasks. After the completion of these tasks, they were asked to list pros and cons for each form of representation, and rate each of the two representations using the scale introduced in (Lohse et al., 1994). All interaction tasks were recorded using Camtasia 9. Mouse movement and keyboard input were recorded using RUI-Recording User Input<sup>3</sup>. The participants took in average 35 minutes to complete the tasks and fill-in the questionnaires. The study was approved by the institutional ethics board at the Institute for Geoinformatics and ran from July 24<sup>th</sup> till August 2<sup>nd</sup>, 2018. Screenshots of the representations used during the study are provided in the Appendix;
- **Participants:** 17 participants (seven female), from diverse backgrounds, took part in the study. One participant took much more time (requiring much assistance during the study) and his data was removed from the analysis. Figure 3 shows background information about the remaining 16 participants (9 male, 7 female).

As the figure illustrates, the participants were mostly young, but had a quite heterogeneous background with respect to profession, use of OGD, interaction with geovisualization, place of living, and familiarity with the city districts of Münster.

Figure 3. Background information about the participants



### 4.3. Results

- **Accuracy:** Table 4 presents the overall accuracy rates obtained for both representations. Accuracy here denotes the proportion of correct answers provided by the participants, and as one can see, the accuracy rates were high, and similar in both conditions. An analysis of almost 1200 usability tasks showed that the average task-completion rate is 78% (Sauro, 2011). The fact that accuracies (and thus task-completion rates) were high in both conditions (and beyond that benchmark value) suggests that both representations are usable (i.e. appropriate) for the given OGD information search tasks;
- **Time-based efficiency:** Time-based efficiency refers to the time taken by the participants to complete the information search tasks. Table 5 presents the average durations per tasks and Figure 4 informs about the variations per task and participants. R and lme4<sup>4</sup> were used to perform a linear model analysis of the relationship between ‘representation’ and ‘time’ taken to find answers to the questions. First, to test for the interdependencies between the two variables of representation

**Table 4. Accuracy per task and representation (in percentage)**

	T1	T2	T3	T4	T5	T6	Average Overall Accuracy
Geovizualization1 (A4)	100	100	100	87.5	87.5	100	95.8
Geovisualization2 (A6)	87.5	87.5	87.5	87.5	100	100	91.7
<i>Average accuracy per Task</i>	<i>93.75</i>	<i>93.75</i>	<i>93.75</i>	<i>87.5</i>	<i>93.75</i>	<i>100</i>	
Table1 (D4)	87.5	100	100	87.5	100	100	95.8
Table2 (D6)	75	100	100	87.5	87.5	100	91.7
<i>Average accuracy per Task</i>	<i>81.25</i>	<i>100</i>	<i>100</i>	<i>87.5</i>	<i>93.75</i>	<i>100</i>	

**Table 5. Time-based efficiency per task and representation in seconds (values in the table are rounded to the first decimal place)**

	T1	T2	T3	T4	T5	T6	Average Overall Efficiency
Geovizualization1 (A4)	37.3	15.6	10.3	40.0	18.5	18.0	23.3
Geovisualization2 (A6)	63.8	13.1	8.7	76.9	51.7	16.7	38.5
<i>Average efficiency per Task</i>	<i>50.6</i>	<i>14.4</i>	<i>9.5</i>	<i>58.4</i>	<i>35.1</i>	<i>17.4</i>	
Table1 (D4)	32.4	14.7	9.9	155.6	25.2	11.5	41.6
Table2 (D6)	42.4	17.3	16.1	128.6	22.8	12.4	39.9
<i>Average efficiency per Task</i>	<i>37.8</i>	<i>16.0</i>	<i>13.0</i>	<i>142.1</i>	<i>24.0</i>	<i>11.9</i>	

and task, a linear mixed model, with fixed effects being representation and task, and subjects (i.e. participants) as random effect was used (see below):

InfoSearch.model = lmer (time ~ representation\*task + (1|subject), data = ....)

The interaction between representation and task was significant ( $\chi^2(15) = 31.605, p=0.0072$ ), indicating that the time taken for info search in the context of OGD is *a factor of both task and representation*. Next, six linear models (one per task) of time as a function of representation were built, to shed some light on the within-representation differences when it comes to task performance. The models were not significant for T1, T2, T3, and T5. On the contrary they were significant for T4 ( $F(1, 26) = 4.65, p=0.04$ ) and T6 ( $F(1, 29) = 9.648, p=0.004$ ). In particular, participants using the geovisualizations were 59% faster for T4 (95% confidence interval [3%, 115%]), while participants using the data tables were 46% faster during T6 (95% confidence interval [16%, 76%]).

- **User-ratings of the two representations:** Lohse et al. (1994) used 10 scales to ask users to rate 11 different types of representations. All representations were static, that is, there is still a need of replicating their study to unveil properties of representations in the digital age, which are mostly interactive. Since the 10 scales they used in their work were independent, they were re-used to assess the differences between the two types of representations examined in this work. Table 6 presents the results. ICC (intra-class-correlation) values were computed using the icc package in R<sup>5</sup>, to get an idea of the percentage of agreements between the two groups of participants (ours and those from (Lohse et al., 1994)). ICC is one of the most commonly-used statistics for assessing inter-rater agreements for ordinal, interval, and ratio variables, and is

Figure 4. Variations of the times taken by the participants, per task and representation

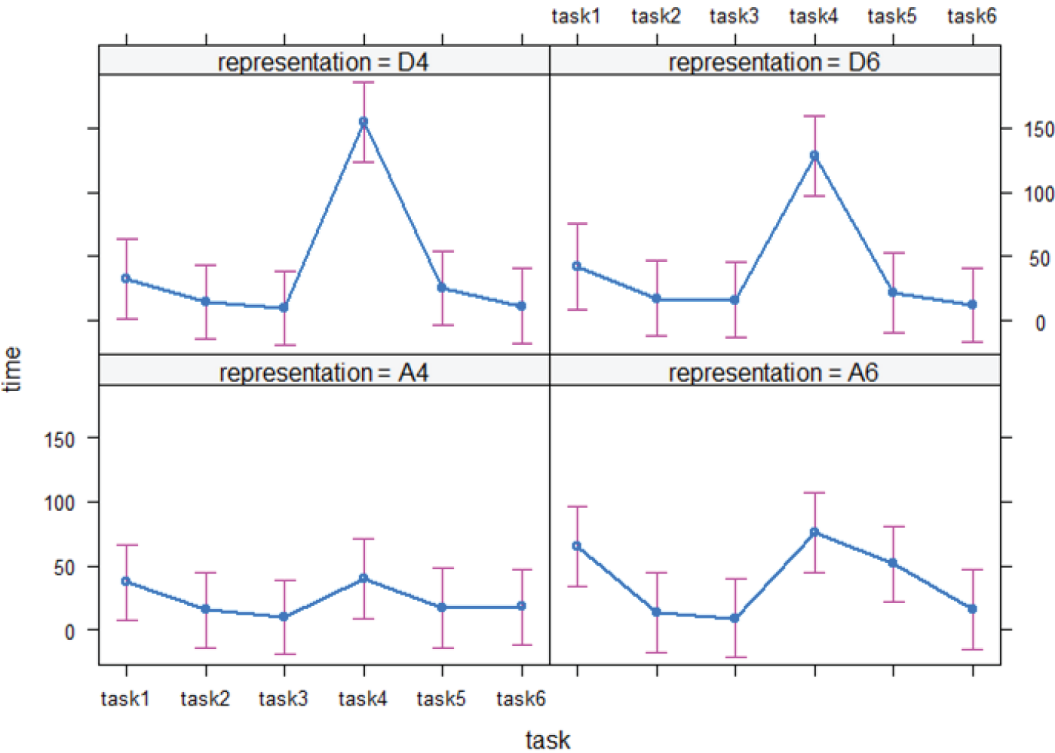


Table 6. User ratings reported in Lohse et al (maps/tables), and those from the participants in the study (Geovisualizations, table-based representation)

	1 Spatial 9 Nonspatial	1 Nontemporal 9 Temporal	1 Hard 9 Easy	1 Concrete 9 Abstract	1 Continuous 9 Discrete	1 Attractive 9 Unattractive	1 Parts 9 Whole	1 Nonnumeric 9 Numeric	1 Static 9 Dynamic	1 A Lot 9 A Little
Maps	1.9	2.0	7.5	3.6	4.3	3.9	4.5	3.8	2.4	2.7
Geovisualizations	1.9	6.8	7.7	3.3	3.8	2.3	6.0	4.8	7.9	3.4
Tables	7.1	1.8	5.1	5.1	5.4	5.2	2.5	8.0	2.4	2.8
Table-based representation	7.8	7.4	7.4	2.3	3.9	5.4	4.5	8.6	1.1	2.8

thus appropriate for this study (the 10 scales are on an ordinal level). For the ICC computation, the unit of analysis is ‘average’ (the ratings are averaged over the participants in both studies respectively), and the type of model is ‘two-way’ (the same subjects rated all representations) in line with recommendations from previous work (Hallgren, 2012). The ICC values were computed for ‘absolute agreement’ and were 0.431 (confidence interval [-0.805, 0.849]) for the geovisualizations and 0.679 (confidence interval [-0.275, 0.92]) for the data tables.

A linear mixed model analysis of the relationship between representation and ratings was done to assess the differences between the two representations from the participants' point of view. 10 models (one per rating dimension) were built, with representation as fixed effect, and the participant as random effect. The models were significant on five dimensions (each of these dimensions were originally defined in (Lohse *et al.*, 1994) as the type of knowledge conveyed by the representation): spatial ( $\chi^2(1) = 55.014$ ,  $p < 0.001$ ), attractive ( $\chi^2(1) = 18.624$ ,  $p < 0.001$ ), part-whole ( $\chi^2(1) = 5.006$ ,  $p = 0.026$ ), numerical ( $\chi^2(1) = 40.502$ ,  $p < 0.001$ ) and dynamic ( $\chi^2(1) = 97.494$ ,  $p < 0.001$ ). The models were not significant on the other five dimensions (i.e. temporal knowledge, understandability, degree of abstraction, expression of continuous relationships, and amount of information).

- **User-feedback about the two representations:** Table 7 summarizes the feedback provided by the users on the pros and cons of both types of representations. The clear layout of the geovisualization and its easing of the comparison of districts were most frequently mentioned by the users as positive features. On the contrary, the users pointed out that the structure of the geovisualization is less clear (i.e. not as predictable as that of the table), and reported the need to use the mouse to see some map labels as negative. Positive features most often mentioned for the table include the easy comparison of attribute values and the clear structure, while negative features most frequently listed were the absence of spatial information (both the locations of the districts and the spatial relationships between districts) and the ordering of districts/city districts (which was not deemed most intuitive).

## 5. DISCUSSION

From the preceding section and the accuracy values obtained, both geovisualization and table-based representations are suitable for information search in the OGD landscape. Given that both representations performed differently when it comes to the time needed to find information, one can

Table 7. Participants' positive and negative feedback about the two representations, with their respective frequencies

Geovisualizations		Data Table	
Positive	Negative	Positive	Negative
Clear layout (8)	Structure less clear (4)	Comparison of attribute information is easy (7)	No spatial information (8)
Easy comparison of the districts (5)	Needs mouse hover to display names (3)	Clear structure (6)	Arrangement/Ordering of city districts and districts (7)
Appealing visuals (4)	Searching takes more time when one does not have local knowledge about the locations of the districts (2)	All information at one look (6)	Tendencies are not evident on a first look (2)
User friendly / Intuitive (4)	Precise numbers not immediately visible (2)	Italic and bold emphasis (3)	No interaction possible to sort the data (1)
Selection of specific information possible (3)	Search function missing (2)	Easy to understand (2)	Boring presentation (1)
Tendencies more accessible (2)	Comparison of attribute information more laborious (2)	Uniform data (1)	The amount of numbers is overwhelming (1)
Interactivity (1)	Bubble map does not help if attribute values are similar (1)	Search function of PDF file (1)	
	Comparison of years missing (1)		
	Scrolling of the map necessary to see more (1)		



conclude that they make different types of information more visible. Both types of representation seem to present no difference when it comes to space-alone, attributes-in-space, and space-in-time questions at the elementary level (i.e. identify questions in Table 3). Geovisualizations seem to be more appropriate for space-alone questions which a comparison objective, while data tables seem to be more adequate for space-in-time comparison questions. That the tables performed better here is a bit surprising since one component of the geovisualizations was histograms, which accounted for temporal variations in the data (see Figures 5-8 in the Appendix). None of the two representations could offer a significant gain in time when it comes to attributes-in-space comparison questions. In some, geovisualizations make space-alone comparison knowledge more visible, while data tables make space-in-time comparison information more visible to users [Takeaway1].

- **User-ratings:** The previous systematic comparison between (static) geovisualizations and (static) data tables from (Lohse et al., 1994) is valuable, but the *icc* values obtained when correlating the static and interactive representations (0.7 for table, and 0.4 for geovisualization) are an indication that the conclusions reached by Lohse and colleagues need to be re-examined in the light of recent technological developments [Takeaway1]. An *icc* of 0.7 indicates ‘good’ agreement, while an *icc* of 0.4 means ‘fair’ agreement (Hallgren, 2012). In addition, the ratings themselves are valuable for research on effective media for data communication. In particular the relevance of such ratings is that they are a way of elucidating the mental representations users intuitively associate with a certain type of representation.

Looking at the user ratings, one can see that each representation has its areas of strengths and weaknesses. According to the users’ assessments [Takeaway3], geovisualizations seem, intrinsically, to make spatial knowledge, the attractiveness of open government data, dynamic knowledge and holistic knowledge more visible. On the contrary, data tables seem to make numerical knowledge more visible. The user ratings are in general consistent with the time-based measurements, and the time-based measurements actually help to refine some of the claims. Taking into account the observations from the previous paragraph, one can conjecture [Takeaway4] that geovisualizations would make holistic knowledge more visible if that knowledge is of type space-alone comparison. They may not be more successful in making holistic knowledge more visible than interactive tables, if the type of knowledge is space-in-time comparison.

- **Implications for open data publishing:** The user ratings can be used to formulate general recommendations to open data publishers<sup>6</sup>. For instance, Table 6 suggests that spatial data should be presented as geovisualizations to citizens (people intuitively associate the problem of communicating spatial knowledge with geovisualizations) and that numerical data should better be presented as table. A recommendation to open data publishers that can be drawn from this [Takeaway5] is that geovisualizations representing numerical data should offer an alternative view of the data as table to users. Numerical data involving spatial information should, whenever possible, be accompanied by geovisualizations. Interestingly, many of the participants mentioned the absence of spatial information as one of the drawback of the data table (see Table 7), when in fact the spatial information was *in* the table. That is, data tables may not simply fail to convey spatial information, they can also obscure the very fact that spatial information is present.

Another recommendation to open data publishers that can be extracted from the table [Takeaway6] is that publishers can take advantage of geovisualizations to stress the attractiveness of open data to the general public. In addition (and consistent with intuition), greater understandability, appropriate degree of abstraction, and adequate amount of information seem much less intrinsic to either type of representation (see Section 4.3). Open data publishers should thus devise strategies to maximize these features on a case-by-case basis.

- **Methodical aspects of representation comparison:** As indicated by the cognitive fit theory (Vessey, 1991), matching (a) problem representation to mental representation and (b) mental representation to task, could predict the performance of information presentation formats on specific tasks. ‘Problem representation’ denotes the way the information is presented to the user (i.e. geovisualization or data table), while ‘task’ refers to the specific task the user has to perform (i.e. in this case, information finding); ‘mental representation’, according to (Vessey, 1991), is the way the problem is represented in human working memory. The user ratings are primarily useful for a better understanding of (a) and they can help to predict the performance of information presentation formats on tasks. Since the user ratings touch upon eleven dimensions, they enable a much higher number of predictions than the spatial-symbolic dichotomy suggested by Vessey (i.e. graphs are expected to perform better than tables on spatial tasks, tables expected to perform better than graphs on symbolic tasks).

User ratings need to be complemented by empirical investigations of the sort done in this work, based on empirically derived taxonomies as the one proposed in (Roth, 2013a), to get a complete picture of the merits of a representation. For instance, the ratings suggest that users intuitively associate geovisualizations (more than they do with data tables) to the communication of holistic spatial knowledge, yet, space-in-time comparison information was retrieved faster through data tables. That is [Takeaway7], the framework User Ratings + Benchmark Tasks is useful to gather further insights on different types of representations, on the roads towards general theories of media effectiveness in the OGD context. As discussed in (Whetten, 1989), a complete theory has four components: the ‘what’ (i.e. relevant concepts), the ‘how’ (i.e. relationships between the concepts), the ‘why’ (i.e. underlying factors justifying the relationships between concepts) and the ‘who, where and when’ (i.e. boundaries of generalizability of the theoretical propositions). In this work, the User Ratings have helped to partially formulate the ‘what, how and why’ (e.g. geovisualizations make holistic spatial knowledge more visible to users than data tables, because they provide a better fit to their mental representations). The Benchmark Tasks helped to specify the sensitivity to context (e.g. geovisualizations may be more successful in making holistic knowledge more visible than interactive tables, if the type of knowledge is space-alone comparison). The User Ratings + Benchmark Tasks framework used in this work is thus a promising technique for a further investigation of strengths and weaknesses of media in the OGD context (and beyond).

- **Interaction as an important dimension of graph vs table comparison:** Previous work (Coll, Coll and Thakur, 1994) has compared the relative efficiency of tables and graphs (i.e. bar charts) and arrived at the conclusion that the use of data in a graph form is superior than the use of data in table form, when the task involves the retrieval of relational information. Use of table is more efficient when the task involves the retrieval of specific value (Coll, Coll and Thakur, 1994). The results show that this conclusion does not extrapolate entirely to the case of interactive geovisualization vs interactive data tables. A possible reason could be that interaction as a dimension was left out of the study aforementioned. Research on the overall effect of interactivity on cognition in the Web is still lacking consensus (see Yang and Shen, 2017), but interactivity is a dimension which can potentially influence information search results. Put differently [Takeaway8], findings in the graph vs table literature should be refined in light of the recent developments in the information era (and the ensuing possibilities for interactivity), with a controlled assessment of the impact of interactivity. Evidence for this need in the current work<sup>7</sup> is the substantial difference between user ratings from Lohse et al and those provide by users in the current work, on the ‘dynamic knowledge’ dimension. As Table 6 shows, there was no difference perceived by users regarding the two representations back in 1994, but there is a gulf between the two when interaction is added (users rated geovisualization as significantly more ‘dynamic’ than data tables).

- **Limitations:** Wang, Bretschneider and Gant (2005) pointed out that information seeking performance is a co-result of citizens' characteristics, information task attributes, and the web-based application. The relatively homogeneous group with respect to age (i.e. young people), limits the generalizability of the results to the whole population of citizens. Additional evidence is needed (which more diverse age groups, and a higher number of participants) before a definitive statement can be made on the observations made in this work. In addition, the study has only covered two of the six map interaction goals proposed by (Roth, 2013a), and it is likely that the results vary if new types of tasks (i.e. rank, associate or delineate) are included. Contrasting the findings of subsequent studies on these four types of tasks with findings from the existing literature (which mostly touched on 'associate' tasks, e.g. Smelcer and Carmel, 1997; Dennis and Carte, 1998) would be necessary to formulate general conclusions on the respective properties of both types of media.

## 6. CONCLUSION

This article has presented a synthesis of the distinguishing characteristics between geovisualizations and data tables for the purpose of greater transparency enablement in the context of open government data (OGD). Transparency was defined as making information more visible and the article has assessed the capacities of both types of representation in making six types of information visible: space-alone identify, attributes-in-space identify, space-in-time identify, space-alone compare, attributes-in-space compare, and space-in-time compare. A user study with 16 participants led to the observation that both types of representations do not exhibit significant differences on four of the types of information (i.e. space-alone identify, attributes-in-space identify, space-in-time identify and attributes-in-space compare). On the contrary, geovisualizations seem to make space-alone compare information more visible, while the tables make space-in-time compare information more visible to users. The empirical data collected can be used by open data publishers to decide on when to go for one representation or the other, depending on the information search tasks they intend to primarily support.

## ACKNOWLEDGMENT

Auriol Degbelo gratefully acknowledges funding from the European Union through the GEO-C project (H2020-MSCA-ITN-2014, Grant Agreement Number 642332, <http://www.geo-c.eu/>). Tomi Kauppinen gratefully acknowledges Aalto Online Learning (A!OLE), a strategic initiative of the Aalto University, the project which he serves as a project leader.

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## ENDNOTES

- <sup>1</sup> All links were last accessed on November 20, 2018.
- <sup>2</sup> <https://www.stadt-muenster.de/stadtentwicklung/zahlen-daten-fakten.html>
- <sup>3</sup> <http://acs.ist.psu.edu/projects/RUI/>
- <sup>4</sup> <https://github.com/lme4/lme4>
- <sup>5</sup> <https://www.rdocumentation.org/packages/irr/versions/0.84/topics/icc>
- <sup>6</sup> As done earlier for example in (Lohse et al., 1994).
- <sup>7</sup> Detailed information about the background of participants from Lohse et al is not available, and the work has assumed throughout that a comparison of the aggregated rating scores across all participants is meaningful.



APPENDIX: SCREENSHOTS OF THE DIFFERENT  
REPRESENTATIONS USED DURING THE STUDY

Figure 5. Screenshot of population data

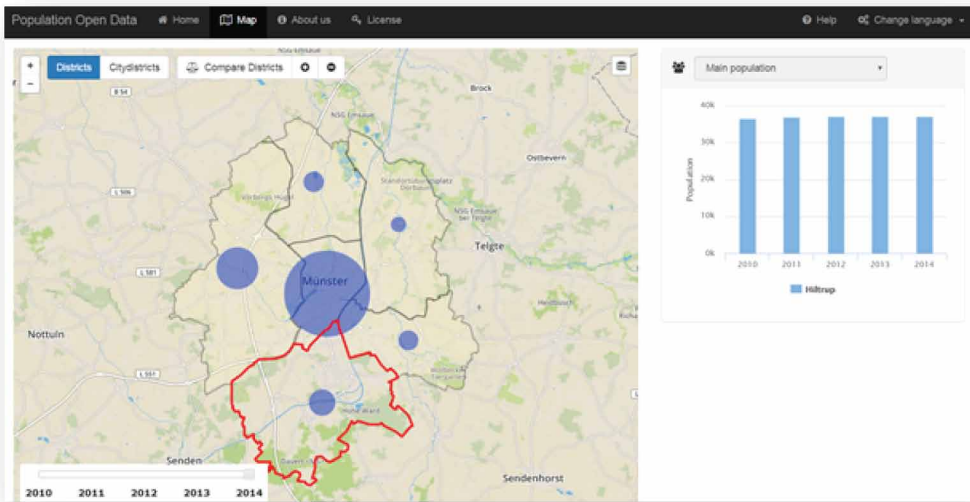


Figure 6. Screenshot of representation used in study

Bevölkerung am Ort der Hauptwohnung 2010 – 2014					
Stadtteil Teilbereich Stadtbezirk	Bevölkerung am Ort der Hauptwohnung in Münster am 31.12.				
	2010	2011	2012	2013	2014
	Anzahl				
11 Aegidii	1 286	1 389	1 401	1 421	1 411
12 Überwasser	1 166	1 322	1 315	1 333	1 324
13 Dom	2 026	2 155	2 139	2 190	2 151
14 Buddenturm	2 119	2 286	2 294	2 367	2 394
15 Martini	1 200	1 310	1 346	1 370	1 364
Altstadt	7 797	8 462	8 495	8 681	8 644
21 Pluggendorf	3 715	4 159	4 227	4 309	4 447
22 Josef	7 497	8 123	8 193	8 537	8 575
23 Bahnhof	962	1 065	1 082	1 178	1 234
24 Hansaplatz	6 255	6 696	6 768	6 762	6 853
25 Mauritz-West	5 641	6 018	6 011	6 116	6 199
26 Schlachthof	4 710	4 993	5 045	5 164	5 215
27 Kreuz	11 319	12 139	12 245	12 307	12 337
28 Neutor	3 509	4 180	4 168	4 164	4 247
29 Schloss	1 947	2 144	2 168	2 198	2 173
Innenstadtring	45 555	49 517	49 907	50 735	51 280
31 Aaseestadt	5 223	5 385	5 447	5 464	5 415
32 Geist	8 494	8 713	8 741	8 774	8 895
33 Schützenhof	6 790	7 298	7 362	7 532	7 606
34 Düesberg	6 720	6 858	6 911	6 968	6 989
Mitte-Süd	27 227	28 254	28 461	28 738	28 905
43 Hafen	928	1 043	1 023	1 049	1 039
44 Herz-Jesu	4 846	5 038	5 079	5 070	5 136
45 Mauritz-Mitte	9 683	9 939	9 922	10 113	10 126
46 Rumphorst	7 684	7 828	7 910	8 000	8 047
47 Upenberg	7 744	8 257	8 397	8 496	8 523
Mitte-Nordost	30 885	32 105	32 331	32 728	32 871
Mitte	111 464	118 338	119 194	120 882	121 700

Figure 7. Screenshot of Münster employees used in study

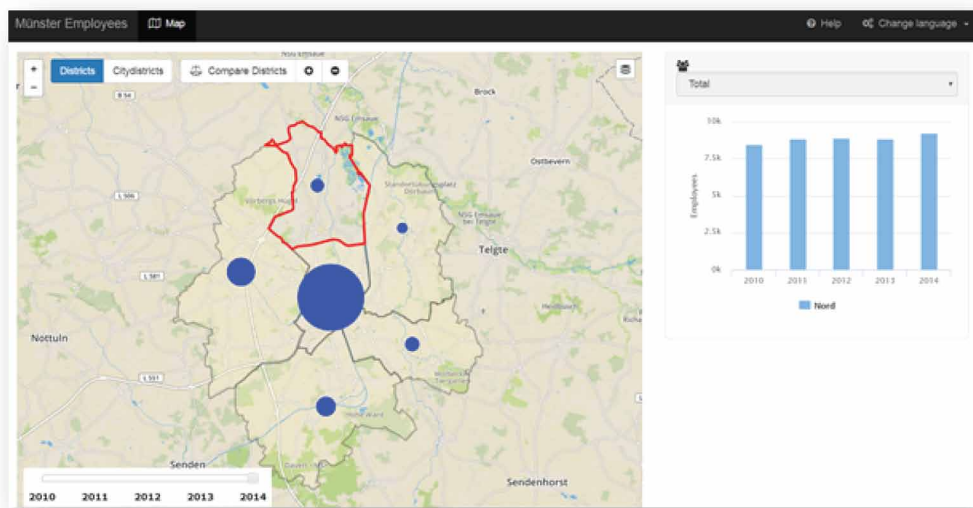


Figure 8. Screenshot of representation used in study

Sozialversicherungspflichtig Beschäftigte					
Stadtteil Teilbereich Stadtbezirk	Sozialversicherungspflichtig Beschäftigte am WOHNORT Münster am 31.12.				
	2010	2011	2012	2013	2014
	Anzahl				
11 Aegidii	436	455	455	464	466
12 Überwasser	429	471	446	445	450
13 Dom	686	742	789	783	811
14 Buddenturm	672	722	727	747	783
15 Martini	444	462	493	511	483
Altstadt	2 667	2 852	2 910	2 950	2 993
21 Pluggendorf	1 418	1 519	1 596	1 654	1 675
22 Josef	3 287	3 470	3 554	3 685	3 773
23 Bahnhof	396	430	461	466	501
24 Hansaplatz	2 842	2 983	3 052	3 042	3 063
25 Mauritz-West	2 283	2 448	2 460	2 518	2 616
26 Schlachthof	1 731	1 878	1 912	1 929	1 946
27 Kreuz	4 234	4 467	4 526	4 538	4 661
28 Neutor	1 285	1 417	1 424	1 454	1 468
29 Schloss	637	684	694	686	684
Innenstadttring	18 113	19 296	19 679	19 972	20 387
31 Aaseestadt	1 684	1 714	1 728	1 798	1 875
32 Geist	3 112	3 221	3 296	3 341	3 481
33 Schützenhof	2 833	3 082	3 135	3 168	3 354
34 Duesberg	2 317	2 385	2 468	2 537	2 591
Mitte-Süd	9 946	10 402	10 627	10 844	11 301
43 Hafen	395	423	469	468	470
44 Herz-Jesu	1 627	1 743	1 776	1 791	1 900
45 Mauritz-Mitte	3 554	3 695	3 775	3 845	3 949
46 Rumphorst	2 666	2 725	2 792	2 902	2 946
47 Uppenberg	2 632	2 805	2 823	2 882	3 009
Mitte-Nordost	10 874	11 391	11 635	11 888	12 274
Mitte	41 600	43 941	44 851	45 654	46 955

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