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Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology



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ABSTRACT

Policy-makers expect that open data will be accepted and used more and more, resulting in a range of benefits including transparency, participation and innovation. The ability to use open data partly depends on the availability of open data technologies. However, the actual use of open data technologies has shown mixed results, and there is a paucity of research on the predictors affecting the acceptance and use of open data technologies. A better understanding of these predictors can help policy-makers to determine which policy instruments they can use to increase the acceptance and use of open data technologies. A modified model based on the Unified Theory of Acceptance and Use of Technology (UTAUT) is used to empirically determine predictors influencing the acceptance and use of open data technologies. The results show that the predictors *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions* and *voluntariness of use* together account for 45% of the variability in people's behavioral intention to use open data technologies. Except for *facilitating conditions*, all these predictors significantly influence behavioral intention. Our analysis of the predictors that influence the acceptance and use of open data technologies can be used to stimulate the use of open data technologies. The findings suggest that policy-makers should increase the acceptance and use of open data technologies by showing the benefits of open data use, by creating awareness of users that they already use open data, by developing social strategies to encourage people to stimulate each other to use open data, by integrating open data use in daily activities, and by decreasing the effort necessary to use open data technologies.

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1. Introduction

All sorts of open data are currently becoming available to the public as they are being published on the internet. The use of these open data can provide considerable advantages to researchers, civil servants and other stakeholders, such as increased transparency (Bertot, Jaeger, & Grimes, 2010), accountability (Parsons et al., 2011), innovation (Janssen, 2011; van Veenstra & van den Broek, 2013), and increased participation of citizens in government activities (Conradie & Choenni, 2014; McDermott, 2010). Open data use refers to the activity that a person or an organization conducts to view, understand, analyze, visualize or in other ways use a dataset that has been provided to the public by a governmental organization. For example, a citizen may use open data by analyzing quality indicators for schools in his neighborhood by using open government data from the school's inspectorate of his country.

Technologies are necessary for making use of open data. The usage process can consist of various steps and often requires the discovery, scrutinization, processing, visualization and evaluation of open data using technology. Yet, the acceptance and use of open data technologies

has shown mixed results. Data providers are encouraged to publish and link their content to generate useful information for the public (Rajabi, Sicilia, & Sanchez-Alonso, 2014), but whereas a large number of datasets is available, only a limited number of datasets is used (Bertot, McDermott, & Smith, 2012). Although encouraging data use is key for open data (Solar, Meijueiro, & Daniels, 2013), and the acceptance of open data technologies is a necessary condition for the creation of value with them, the open data debate has mainly been oriented towards data provision (Foulonneau, Martin, & Turki, 2014) rather than data use. Despite occasional initiatives to stimulate the use of open data technologies using hackathons, workshops and conferences, not much is known about which predictors actually influence people's willingness, ability and intention to use open data technologies. Open data is a relatively new field and the acceptance and use of open data technologies has barely been investigated. Systematic research with sound theoretical foundations about the possible acceptance and use of open data technologies is lacking.

If governments want citizens, entrepreneurs and researchers to use open data technologies, they need to understand under which conditions these stakeholders would adopt open data technologies. Obtaining a better understanding of the drivers of acceptance and use of open data technologies can help to better exploit the full potential of open data and realize its advantages. Insight in the factors influencing open data

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technology acceptance and use can support data providing organizations in making more informed future investment decisions concerning the supply of open data (Davies, 2010). Such insights might help to create decision-making models which optimize the conditions under which data are released to increase the acceptance and use of governmental data and to stimulate the creation of public value. A better understanding of the predictors of the acceptance and use of open data technologies can help policy-makers to determine which policy instruments they can use to increase the acceptance and use of open data technologies, ultimately contributing to high level objectives including transparency, citizen participation and innovation. Furthermore, open data use can be the starting point for democratic dialogs (Davies, 2010), where open data providers and users interact to find out what can be learned from open data use and how this can help governments to improve processes, services and decision-making.

The objective of this study is to obtain insight in the predictors of the acceptance and use of open data technologies. In this paper we focus on the use of 'open data technologies' rather than open data use in general, because technologies are needed to be able to use open data. Without technologies, open data cannot be found, curated, scrutinized, processed, visualized and used. The open data use technologies that are in the scope of this study will be explained in Section 2. Moreover, open data can be used for various purposes, such as transparency, collaboration and participation (Gascó, 2014), yet using open data for the purpose of conducting research, for scrutinizing data and for obtaining new insights has not been studied much before. Therefore, this study focuses on the use of open data technologies for the purpose of research, scrutinizing data and obtaining new insights.

This paper is organized as follows. In the following section we describe the original UTAUT model and our motivation for using it in this study. In addition, we derive hypotheses from an amended UTAUT model and from the literature concerning the acceptance and use of open data technologies. In Section 3 the research approach for empirically testing the hypotheses is presented. In the fourth section we report on the findings from a questionnaire that investigates the extent to which the UTAUT constructs can explain the acceptance and use of open data technologies and test how well the refined UTAUT model explains the acceptance and use of open data technologies. Moreover, we compare the explained variance of our modified model with the original UTAUT model. Based on the findings we discuss recommendations for policy-makers to improve the use and acceptance of open data technologies, and recommendations for further research. Finally, conclusions about the predictors of open data technology acceptance and use are provided.

2. Research model and hypothesis development

UTAUT is a plausible theory for examining the acceptance and use of open data technologies, since it allows for investigating which factors influence Information Technology (IT) surrounding open data, while at the same time taking social factors into account. Martin (2014) states that technologies in the context of open data refer to working configurations "that include tangible artifacts, the skills of technologists and users, and the interfaces of artifacts with the wider technical infrastructure" (p. 225). Examples of open data technologies are linked open data vocabularies including value vocabularies and metadata element sets to assist in open data use (Pattueli, 2012), open data infrastructures and portals, software for transforming, visualizing, analyzing, linking and assessing the quality of datasets, and Application Programming Interfaces (APIs). Social factors, such as the behavior of open data users and influence from and interaction between open data users are important also for the acceptance and use of open data technologies. The significance of investigating social factors in research on technology adoption has been stressed in various articles (e.g. Gwebu & Wang, 2011).

Moreover, UTAUT allows for investigating complex and sophisticated organizational technologies of managerial concern (Venkatesh, Morris, Davis, & Davis, 2003). Open data are characterized by differing

contexts and semantics of open datasets, differences in types and characteristics of datasets, a large number of involved interdependent stakeholders with differences of interests and other contextual factors. Open data technologies are complex and sophisticated, which shows the appropriateness of this UTAUT characteristic for examining open data technology acceptance and use. Recently, UTAUT has also been used in research on factors which influence the intention to use open government (Jurisch, Kautz, Wolf, & Krcmar, 2015), and open data disclosure is often seen as one aspect of an open government.

The acceptance and use of Information Technology (IT) has been of significant importance for Information Systems (IS) research and practice for decades (Lancelot Miltgen, Popovič, & Oliveira, 2013). The UTAUT is one often used model that examines Information Technology acceptance and use. Venkatesh et al. (2003) proposed the UTAUT based on a review of theoretical models and other literature about acceptance of technology and the predictors of this acceptance. The UTAUT can be viewed as a unified model for the investigation of the acceptance and use of technology. It is a well-established theory which has been tested considerably thereafter in many different contexts.

The key idea of the UTAUT is that a number of factors lead to the behavioral intention to accept and use a system or technology, while this behavioral intention in combination with facilitating conditions leads to the actual use of this system or technology (Sykes, Venkatesh, & Gosain, 2009). In the UTAUT model four constructs directly predict the behavioral intention to use Information Technologies (IT), namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC). Additionally, four key moderators are defined, including Gender (G), Age (A), Experience (E) and Voluntariness of Use (VU). The UTAUT model has been praised for its high quality compared to competing models (Shibl, Lawley, & Debuse, 2013). It explains about 70% of the variance in the behavioral intention to use a system or technology, whereas other models explain approximately 40% of the variance (Venkatesh et al., 2003). Behavioral intention is defined here as an individual's intention, prediction or plan to use a technology in the future. Several theoretical models have emphasized that behavioral intention is the best predictor of human behavior (Lee & Rao, 2009).

2.1. Hypothesis development for direct effects

The hypotheses underlying the UTAUT model are often amended to better suit the context of the study (e.g. Curtis et al., 2010; Duyck et al., 2008; Venkatesh, Thong, Chan, Hu, & Brown, 2011). We amended the original UTAUT model to better suit the context of open data, based on relevant literature concerning the acceptance and use of open data technologies. Fig. 1 shows the modified model for open data technology adoption used in this research surrounded by a dashed line. The hypotheses and the modifications are explained in the following paragraphs.

2.1.1. Performance expectancy

Performance expectancy is defined here as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). Prior research shows that performance expectancy and its related constructs are the strongest predictors of behavioral intention (Duyck et al., 2008; van Dijk, Peters, & Ebbens, 2008). For instance, Davis (1989) writes that the extent to which people believe that a certain application is going to help them perform their job better influences whether or not they will use a certain application. Venkatesh and Speier (1999) also acknowledge that the achievement of valued outcomes, such as increased payment and improved job performance, are important motivations for using technologies. In the case of open data this could mean that people are more likely to use traditional ways of working if they believe that open data technologies and applications are not going to help them with performing better or making more money. This idea is supported by research of Kaasenbrood (2013), who suggest that the presence of various hindering factors, including hampered accessibility and a lack

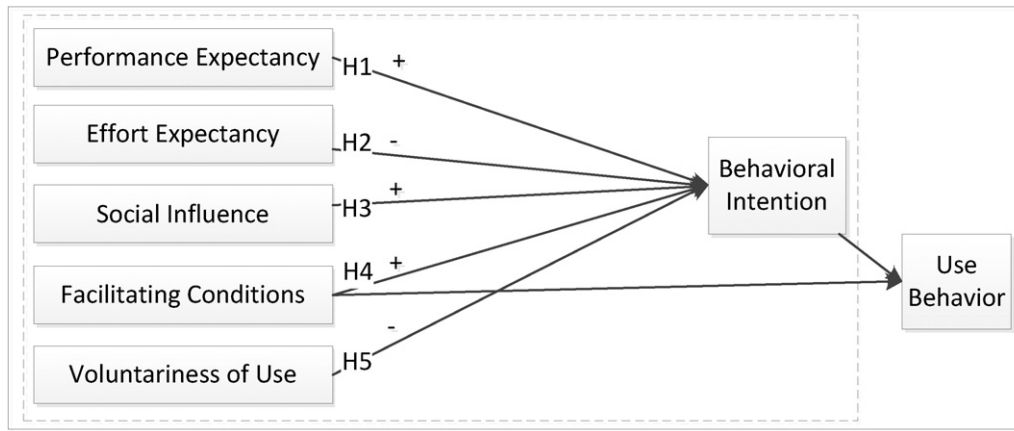


Fig. 1. The modified UTAUT research model.
Source: Adapted from Venkatesh et al. (2003).

of continuity of open data provision, results in companies holding back from solely relying on open government data for their business model. For instance, the lack of user friendly interfaces to open data is believed to deter open data users (Martin, 2014). As a result, there may be large differences with regard to contents and shape of data use for different actors involved in open data (Hunnius, Krieger, & Schuppan, 2014). We believe that the availability of open data technologies, such as open data platforms, software, tools and interfaces, increases an individual's or an organization's expectance to perform better. Thus, consistent with the theoretical arguments underlying UTAUT, we anticipate a direct and positive impact of performance expectancy on the intention to use and accept open data technologies.

H1. Performance expectancy is positively related to the behavioral intention to use and accept open data technologies.

2.1.2. Effort expectancy

Davis (1989, p. 320) found that “even if potential users believe that a given application is useful, they may, at the same time, believe that the system is too hard to use and that the performance benefits of usage are outweighed by the effort of using the application”. Effort expectancy is related to the degree of ease associated with the use of a technology (Venkatesh et al., 2003) and the extent to which a person believes that the use of the technology will be free of effort (Gwebu & Wang, 2011). We define effort expectancy as the extent to which a person or organization believes that using an open data technology will be free of effort. In the context of open data we believe that people analyze their expectations of the extent to which open data systems are easy or difficult to use, and that this perceived ease of use influences their intention to use open data technologies.

Various factors may influence effort expectancy for open data technologies. For instance, locating open government data is complex and accompanied with high costs (Ding, Peristeras, & Hausenblas, 2012), as data are offered at many different infrastructures, and can sometimes be hard to find (Braunschweig, Eberius, Thiele, & Lehner, 2012; Conradie & Choenni, 2014). Datasets are released in numerous different formats (Jeffery, Asserson, Housos, Brasse, & Jörg, 2014; Verma & Gupta, 2012). Moreover, different types of open data, created within a different context, may need a different legal, cultural, or technical treatment. Each context has its own set of characteristics and semantics which influences the way that open data are collected, disseminated, used and interpreted. Furthermore, open datasets can have different quality levels (Petychakis, Vasileiou, Georgis, Mouzakitis, & Psarras, 2014) and can be used for different purposes. Research has shown that OGD suffer from quality issues such as incorrect attribute values (Behkamal, Kahani, Bagheri, & Jeremic, 2014). Due to the large amount of available datasets, their diversity, and the fragmentation of available data, it can be hard to find exactly those

open datasets that one is looking for. Certain datasets may also not be available or accessible (Conradie & Choenni, 2014). Additionally, rights of data use may differ among actors involved in open data (Hunnius et al., 2014). Moreover, Parycek and Sachs (2010) write that skills to use the internet are not uniform among citizens, and Raman (2012) argues that citizens' capabilities to interpret open data may vary. Martin (2014) stresses that potential open data users are often believed to lack the specialist knowledge required to interpret open data. T. G. Davies and Bawa (2012) confirm that people have different capacities to access and use open data, and that these capacities to a certain extent shape the impacts, outcomes and distribution of open government data benefits. The above-mentioned barriers may increase a person's or organization's effort expectancy for open data use and acceptance. Thus, the intention to use an open data technology is theorized to be influenced by perceived ease of use, which is referred to with the term effort expectancy by Venkatesh et al. (2003). Therefore the following hypothesis H2 was generated.

H2. Effort expectancy is negatively related to the behavioral intention to use and accept open data technologies.

2.1.3. Social influence

Social influence is defined as “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, p. 451). Prior research has shown that social influence has an effect on the behavioral intention to use and accept a technology (Venkatesh et al., 2003). We hypothesize that social influence has an effect on the intention to use open data, since colleagues, supervisors and other people could influence whether someone uses an open data system. Efforts dedicated to promote open data to potential users might positively influence the intention to use open data, although it is believed that to-date such efforts are limitedly researched (Martin, 2014). Social influence may also come from management, friends, family and other people who influence the behavior of someone and who are important to this person. In case that open data use is urged by supervisors, managers, teachers or other influential persons, open data use may not be voluntary (for example shown in the case described by Conradie & Choenni, 2012), whereas recommendations of friends and family to use open data can be seen as more voluntary. The following hypothesis H3 was created.

H3. Social influence is positively related to the behavioral intention to use and accept open data technologies.

2.1.4. Facilitating conditions

Facilitating conditions can be defined as “the degree to which an individual believes that an organizational and technical infrastructure

exists to support use of the system” (Venkatesh et al., 2003, p. 453, p. 453). Although prior research has shown that facilitating conditions are not the best predictors for the behavioral intention to use e-government services or for the use of e-government services (Rana, Williams, Dwivedi, & Williams, 2011), we do expect that facilitating conditions influence the intention to use open data. The open data barriers as found in the literature (e.g., Huijboom & van den Broek, 2011) suggest that if facilitating conditions such as networks, connection to internet, sufficient and appropriate open data and appropriate open data infrastructures are available, the intention to use open data will be higher. For example, Parycek and Sachs (2010) write that access to internet may vary among citizens, which suggests that facilitating conditions can differ for an individual's use and acceptance of technologies.

Gurstein (2011) argues that background conditions, such as differences in income, education and literacy, may divide society into two groups, namely those who have access to internet and to open government data which could have significance in their daily lives and those who do not (the so-called “data divide”). For those who do not easily have access to internet and government data and other required resources the facilitating conditions to use in a meaningful way and to accept open data are more limited. For those who do have access to the internet and open public sector data and other required resources, facilitating conditions may be available to a different extent than to others. When facilitating conditions are not in place, the barriers are likely to be too high and, consequently, the intentions of potential open data users to use open data and open data technologies is expected to be lower. As a result we formulated the following hypothesis, H4.

H4. Facilitating conditions are positively related to the behavioral intention to use and accept open data technologies.

2.1.5. Voluntariness of use

Prior research has shown the importance of the above-mentioned four constructs of the UTAUT model of Venkatesh et al. (2003). A fifth construct was added to the model. Whereas in the original UTAUT model voluntariness of use is expected to moderate the effect of social influence on behavioral intention, we hypothesize that voluntariness of use has a direct effect on the intention to use open data technologies. Voluntariness of use is defined as the extent to which persons or organizations believe that their use and acceptance of open data technologies are perceived as voluntary or of free will. The use of open data is driven by the idea that people can voluntarily create value with open data (Jetzek, Avital, & Bjorn-Andersen, 2014). Yet the less voluntarily a person uses open data technologies, the higher his or her intention is to use open data technologies. For some individuals the use of open data technologies may be required because of their job. For instance, when researchers or journalists as part of their job wish to publish text articles which are supported by the visualization of open datasets, their behavioral intention to use open data technologies is higher. If a person is not obligated to use open data technologies, he or she is less likely to actually use open data technologies. This leads to the following hypothesis, H5.

H5. Voluntariness of use is negatively related to the behavioral intention to use and accept open data technologies.

2.2. Moderator effects

Investigating potential moderating variables is of great importance in predicting users' technology acceptance (Sun & Zhang, 2006). However, since our research data do not allow for directly taking into account the moderating variables, we did not design hypotheses for these variables. The data do not provide insight in the moderating effects of gender and age on the direct effects of performance expectancy, effort expectancy, social influence, facilitating condition and voluntariness of use on the behavioral intention to use open data technologies.

We therefore do not extensively discuss the moderating variables in our research model. However, the data do allow for conducting more simple tests regarding the differences in means of the direct predictors of the acceptance and use of open data technologies for genders and ages, which provides some suggestions regarding gender and age differences for performance expectancy, effort expectancy, social influence, facilitating condition and voluntariness of use. These tests are discussed in Section 5.2.

3. Method

In this section the design of the research is presented. The questionnaire and data collection, surveyed open data technologies, the population and the data analysis are discussed.

3.1. Questionnaire and data collection

A questionnaire was developed to obtain information about the acceptance and use of open public sector data from actual users of these data. For each construct of the UTAUT research model, a number of questions were asked, or the respondents were asked to point out on a five-point Likert scale to which extent they agreed with the statement, ranging from “strongly disagree” to “strongly agree” (see Appendix A). The survey questions were mainly based on questions that were already tested by Venkatesh et al. (2003), Venkatesh and Zhang (2010) and Duyck et al. (2008). However, some questions were slightly changed. For instance, one item used by Venkatesh et al. (2003) to measure performance expectancy is “I would find the system useful in my job”. Since our questionnaire was also answered by individuals who did not use open data as part of their job (e.g. citizens), this question was not appropriate for our survey. Some other questions were removed, because they were not appropriate in the context of this survey. For example, one item used by Venkatesh et al. (2003) to measure performance expectancy is “if I use the system, I will increase my chances of getting a raise”. Since our questionnaire was also answered by individuals who did not use open data as part of their job, this question was not included in our survey.

The questionnaire was distributed at four open data conferences and handed out to conference participants. A link to the website of the online questionnaire was sent to e-mail lists, placed on several websites and LinkedIn groups. The questionnaire was disseminated between April and September 2012. In this way a specific group was surveyed. In interpreting the results of this study it is important to keep in mind that the questionnaire was mainly completed by researchers, citizens and civil servants from the social science domain in various countries.

3.2. Open data technologies

In the survey open data were defined as all types of open governmental and public sector data, including geographic, legal, meteorological, social, transport, business and other data. Several examples were given for each of these types of open data. It was explicitly stated that open data from the public sector include any type of public sector data (e.g. governmental data and data from municipalities) or public sector data linked to other data that are published on websites available to anyone. Examples of open data technology that were questioned in the survey include search engines, Application Programming Interfaces (APIs), metadata, the linkage of publications to datasets, open data portals, technologies for transforming, visualizing, analyzing, linking and assessing the quality of datasets and other technologies that are needed to access and use open data. For some technologies, such as APIs and metadata, an explicit definition was given in the survey. To make the survey questions short, understandable and easy to read for the respondents, a number of questions in our survey did not explicitly ask about the use of open data technologies. However, during the introduction of the survey the focus on open data technologies was emphasized.

3.3. Population

Some respondents did not provide answers to all questions. These respondents were deleted from the sample. Some respondents stated that they did not have enough experience with the use of open data to answer the questionnaire completely. Completing the questionnaire took approximately 20 min, which may be a reason why a part of the respondents did not complete the questionnaire. The results that we report on below include information of persons who were open data users and completed the whole survey. In total 111 questionnaires were used in the analyses.

3.4. Data analysis

For analyzing the data, first Cronbach's alpha was used to measure the consistency of the constructs of the model. Then Principal Component Analysis was used to investigate the extent to which the total variance of the model was explained by the predictors included in the model. Varimax factor rotation was used to examine the loading of the predictors. We were constrained by the amount of data that was gathered and the number of responses. Regression Analysis was used to test the hypotheses. Structuration Equation Modeling (SEM) could not be used because most of the literature suggests that a minimum of 200 responses is needed in order to have reliability on findings obtained from the analyses. Additionally, we investigated the moderators of the UTAUT model. A t-test was used to investigate whether there were significant differences between the means of the results of men and women. Finally, the Analysis of Variance (ANOVA) was used to investigate whether there were significant differences between the means of respondents with different ages, the different types of data they used and the purposes they had for using open data.

4. Findings on the acceptance and use of open public sector data

In this section we describe the general characteristics and background of the respondents, the findings on testing the model and the results of testing the original UTAUT model. These findings are described here and discussed more in detail in Section 5.

4.1. Descriptives

Characteristics and background information of the respondents who filled out the questionnaire is provided in Table 1. About three-quarters of the respondents who used open public sector data were men, and about three-quarters of all respondents were between 26 and 50 years old. Most respondents work in social sciences, mainly in political science, public administration, sociology and other social science domains. One third of the respondents monthly used open public sector data, while 27% used them weekly and 26% yearly. Almost 13% of the participants used open public sector data daily or multiple times per day. The key purposes for the respondents to use open public sector data that were assessed as (very) important were to perform statistical analysis, for data linking (combining and integrating different datasets), to write academic publications and to perform policy research.

4.2. Model testing

In this section we report on the results of testing the modified UTAUT model. First, a reliability and validity analysis is discussed, and second we report on the results from the Varimax factor rotation. Thereafter the test results of the modified UTAUT model are presented, and then the original UTAUT model test results are compared with those of the modified UTAUT model.

Table 1
Characteristics and background information of respondents (n = 111).

Respondent characteristic		
Gender	Male	76.6%
	Female	23.4%
Age	22–25 years old	8.1%
	26–30 years old	27.0%
	31–40 years old	24.3%
	41–50 years old	21.6%
	51–60 years old	13.5%
	61 years old or over	5.4%
Primary field of work	Social sciences	46.8%
	Natural sciences	7.2%
	Non-scientific (semi-)governmental (e.g. federal government or municipality)	18.0%
	Non-scientific industry (e.g. private company)	16.2%
	Other	11.7%
Frequency of open public sector data use	Daily or multiple times per day	12.6%
	Weekly or a few times per week	27.0%
	Monthly or a few times per month	33.3%
	Yearly or a few times per year	26.1%
	Do not know	0.9%
Respondents' purposes of open public sector data use	To perform statistical analysis	77.4%
	For data linking (combining and integrating different datasets)	70.2%
	To write academic publications	68.4%
	To perform policy research	63.9%
	To perform investigations (non-scientific and non-policy)	58.5%
	For political and policy-making decisions	54.0%
	For curiosity and/or recreation	51.3%
	For daily operation in work	45.9%
	For news reporting	41.4%
	Other purposes	9.9%

4.2.1. Reliability and validity analyses

Cronbach's alpha was used to measure the consistency of the constructs of the model. This value is also known as the reliability coefficient. Table 2 shows Cronbach's alpha values for the six constructs that are used in our model. Seven of the eight values are above 0.7. Values of 0.7–0.8 are acceptable values for Cronbach's alpha (Field, 2005, p. 668). Two variables were removed from the construct Voluntariness of Use, namely VU3 and VU4, since this increased the alpha value of the construct. No other variables were removed from the constructs. It can be seen in the table that Facilitating Conditions has the lowest alpha value and that removing any item for this construct will not increase Cronbach's alpha. For this reason, we accepted an alpha value of 0.63 for the construct Facilitating Conditions.

4.2.2. Varimax factor rotation

Principal Component Analysis was performed, and the loading of the variables on each factor was calculated by using orthogonal Varimax factor rotation. The Varimax factor rotation showed two low values when the modified model that was presented in Section 3.3 was used. Effort Expectancy statement 4 (“I do not have difficulty in explaining why using open public sector data may be beneficial”) and Facilitating Conditions statement 1 (“I have the resources necessary to use open public sector data”) both had a loading of 0.450. Both variables were removed from the model. After removing these variables, the lowest

Table 2
Cronbach's alpha values for the constructs used in our model.

Construct	# of Items	Alpha
Behavioral Intention (BI)	3	0.83
Performance Expectancy (PE)	4	0.81
Effort Expectancy (EE)	4	0.76
Social Influence (SI)	3	0.82
Facilitating Conditions (FC)	3	0.63
Voluntariness of Use (VU)	2	0.81

Table 3
Overview of the hypotheses.

Hypothesis number	Hypotheses	Supported/not supported
H1	Performance expectancy is positively related to the behavioral intention to use and accept open data technologies.	Supported
H2	Effort expectancy is negatively related to the behavioral intention to use and accept open data technologies.	Supported
H3	Social influence is positively related to the behavioral intention to use and accept open data technologies.	Supported
H4	Facilitating conditions are positively related to the behavioral intention to use and accept open data technologies.	Not supported
H5	Voluntariness of use is negatively related to the behavioral intention to use and accept open data technologies	Supported

Table 4
Multiple regression (n = 111).

Modified model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Standard error	β		
Constant	1.913	.395	–	4.84	.000
Performance Expectancy	.405	.069	.450**	5.89	.000
Effort Expectancy (without EE4)	.116	.056	.161*	2.06	.042
Social Influence	.151	.040	.284**	3.74	.000
Facilitating conditions (without FC1)	.014	.036	.031	.40	.693
Voluntariness of use	–.091	.044	–.163*	–2.07	.041

Note $R^2 = .45$ ($ps < .001$).

* $p < .005$.

** $p < .001$.

loading was 0.77, which means that the loadings are appropriate. In the following sections we report on the modified model in which these two variables are removed.

4.2.3. Hypothesis testing

Table 3 provides an overview of the hypotheses that were tested in this study. In this section these hypotheses are discussed and the results from the regression analysis are presented.

Table 4 shows the outcomes of the multiple regression. The table reveals that the predictors of the modified model account for 45.0% of the variability of the behavioral intention to use open data technologies.

Table 5
Performance Expectancy.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Don't know	Total
Using open public sector data is of benefit to me (PE1).	0% (0)	0% (0)	1.8% (2)	36.9% (41)	59.5% (66)	1.8% (2)	100% (111)
Using open public sector data will enable me to accomplish my research more quickly (PE2).	0% (0)	1.8% (2)	11.7% (13)	34.2% (38)	45.9% (51)	6.3% (7)	100% (111)
Using open public sector data will increase my productivity (PE3).	0% (0)	1.8% (2)	18.9% (21)	37.8% (42)	37.8% (42)	3.6% (4)	100% (111)
Using open public sector data improves my performance in my job (PE4).	0% (0)	1.8% (2)	22.5% (25)	38.7% (43)	32.4% (36)	4.5% (5)	100% (111)

Table 6
Effort Expectancy.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Don't know	Total
It will be easy for me to become skilful at using open public sector data (EE1).	0% (0)	6.3% (7)	24.3% (27)	48.6% (54)	16.2% (18)	4.5% (5)	100% (111)
Learning to use open public sector data will be easy for me (EE2).	0% (0)	7.2% (8)	18.9% (21)	55.0% (61)	16.2% (18)	2.7% (3)	100% (111)
I clearly understand how to use open public sector data (EE3).	0% (0)	13.5% (15)	23.4% (26)	47.7% (53)	12.6% (14)	2.7% (3)	100% (111)

The strongest predictors of the model are performance expectancy and social influence ($p < .001$). This is in line with prior research which has also shown that performance expectancy and related constructs are the strongest predictors of behavioral intention (Duyck et al., 2008; van Dijk et al., 2008). Our findings reveal that the higher the user's expectation to perform well with open data technologies, the higher the behavioral intention to use it. With regard to the performance expectancy, 96.4% of all respondents stated that they agreed (36.9%) or even strongly agreed (59.5%) with the statement "using open public sector data is of benefit to me" (PE1). None of the respondents disagreed with this statement. The majority of the respondents also agreed (34.2%) or strongly agreed (45.9%) with the statement "using open public sector data will enable me to accomplish my research more quickly" (PE2). Only 1.8% of the respondents disagreed with this statement. Most respondents also agreed (37.8%) or strongly agreed (37.8%) with the statement that "using open public sector data will increase my productivity" (PE3). Moreover, many respondents believe that using open public sector data improves their performance in their job (PE4) (71.1%). These results show that *Hypothesis 1, performance expectancy is positively related to the behavioral intention to use and accept open data technologies*, is confirmed ($p < .001$) (see Table 5).

Effort expectancy negatively influences behavioral intention to use open data technologies, meaning that the lower the effort expectancy is to use open data technologies, the higher the behavioral intention is to use open data technologies. Most respondents agreed (48.6%) or strongly agreed (16.2%) with the statement that it will be easy for them to become skillful at using open public sector data. About 55% agreed and 16.2% strongly agreed that it would be easy for them to learn to use open public sector data. The majority of the respondents agreed or strongly agreed that they clearly understand how to use open public sector data. None of the respondents disagreed with any of the statements related to effort expectancy. The foregoing shows that *Hypothesis 2, effort expectancy is negatively related to the behavioral intention to use and accept open data technologies*, is confirmed ($p < .005$) (see Table 6).

Social influence positively influences the behavioral intention to use open data technologies, meaning that the higher the social influence is to use open data, the higher the behavioral intention is to use open data technologies. Most respondents neither disagreed nor agreed with the statements that people who influence their behavior (in general) think that they should use open data (34.2%) or that people who are important to them (e.g. family, friends) think that they should use open data (45.0%). The majority of the respondents agreed with the statement that people who are important to them (e.g. colleagues) think that they should use open data (35.1%) or they neither agreed nor disagreed with this statement (30.6%). *Hypothesis 3, social influence is positively related to the behavioral intention to use and accept open data technologies*, is confirmed ($p < .001$) (see Table 7).

Table 7
Social Influence.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Don't know	Total
People who influence my behavior think that I should use open public sector data (SI1).	0.9% (1)	12.6% (14)	34.2% (38)	28.8% (32)	11.7% (13)	11.7% (13)	100% (111)
People who are important to me (e.g. family, friends) think that I should use open public sector data (SI2).	7.2% (8)	21.6% (24)	45.0% (50)	8.1% (9)	4.5% (5)	13.5% (15)	100% (111)
People who are important to me (e.g. colleagues) think that I should use open public sector data (SI3).	1.8% (2)	11.7% (13)	30.6% (34)	35.1% (39)	11.7% (13)	9.0% (10)	100% (111)

Table 8
Facilitating Conditions.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Don't know	Total
Open public sector data is compatible with other systems that I use (FC2).	2.7% (3)	13.5% (15)	25.2% (28)	34.2% (38)	11.7% (13)	12.6% (14)	100% (111)
A specific person or group is available for assistance with difficulties concerning the use of open public sector data (FC3).	16.2% (18)	27.9% (31)	22.5% (25)	13.5% (15)	2.7% (3)	17.1% (19)	100% (111)

Table 9
Voluntariness of use.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Don't know	Total
Although it might be helpful, using open public sector data is certainly not compulsory for my research or other activities (VU1)	9.9% (11)	37.8% (42)	27.0% (30)	19.8% (22)	2.7% (3)	2.7% (3)	100% (111)
My research and other activities do not require me to use open public sector data (VU2)	17.1% (19)	44.1% (49)	21.6% (24)	12.6% (14)	2.7% (3)	1.8% (2)	100% (111)

The fourth hypothesis showed the expectation that facilitating conditions influence behavioral intention. It was found that of all the variables, only the factor facilitating conditions did not have a significant influence on the behavioral intention to use open data ($p > .005$). Thus, *Hypothesis 4, facilitating conditions are positively related to the behavioral intention to use and accept open data technologies*, is not supported. This finding is in line with previous research which showed that facilitating conditions are not the best predictor for behavioral intention to use e-government services or for the actual use of e-government services (Rana et al., 2011). Table 8 reveals that the majority of the respondents agreed that open public sector data is compatible with other systems that they use (34.2%). This table also shows that most respondents do not have access to a specific person or group who can assist them with difficulties concerning the use of open public sector data, as 27.9% of the respondents disagreed with this statement and 16.2% strongly disagreed. In addition, many respondents did not know whether such an assisting person or group was available (17.1%) (see Table 8).

Voluntariness of use negatively influences the behavioral intention to use open data. The more voluntary the use of open data is, the lower the intention is to use open data. Many respondents (47.7%) indicated that their use of open data is not compulsory for their research or other activities. *Hypothesis 4, voluntariness of use is negatively related to the behavioral intention to use and accept open data technologies*, is supported ($p < .005$) (Table 9).

4.2.4. Moderating variables

In addition, several tests were conducted to investigate the role of the moderating variables. Although we could not directly take into account the moderating variables, the data did allow for conducting more simple tests regarding the differences in means of the direct predictors of the acceptance and use of open data technologies for different genders and ages. A t-test was conducted to find out what the differences are between the scores of women and men on the predictors of the modified UTAUT model. On average, female respondents experienced more facilitating conditions ($M = 3.88, SE = 0.25$), than male respondents ($M = 3.29, SE = 0.13$). This difference was significant ($t(109) = 2.124, p < 0.05$). No other significant differences were

found between the means of the factor scores of men and women. Finally, we checked whether the means of the different age groups were significantly different from each other. The results from our Analysis of Variance (ANOVA) showed that there were no significant differences between the age groups. These findings, however, do not provide insight in the moderating effects of gender and age on the direct effects of performance expectancy, effort expectancy, social influence, facilitating condition and voluntariness of use on the behavioral intention to use open data technologies.

4.3. Testing the original UTAUT model

In the previous section we presented the results of the modified UTAUT model. In this section we compare these results to the original UTAUT model. Since we were not able to integrate the moderating variables in our modified model, we will compare our model to the original UTAUT model without these. Since Venkatesh et al. (2003) stated that in the presence of effort expectancy constructs the facilitating condition constructs become non-significant in predicting intention, we removed facilitating conditions from this model. Table 10 provides the multiple regression results of the original UTAUT model without facilitating conditions.

Table 10
Multiple regression (n = 111).

Original model	Unstandardized coefficients		Standardized coefficients	T	Sig.
	B	Standard Error	β		
Constant	1.560	.363		4.299	.000
Performance Expectancy	.422	.068	.469**	6.241	.000
Social Influence	.166	.040	.312**	4.133	.000
Effort Expectancy	.124	.062	.147*	1.998	.048

Note $R^2 = .429 (ps < .001)$.
* $p < .005$.
** $p < .001$.

Table 10 reveals that the predictors of the original UTAUT model account for 42.9% of the variability of the behavioral intention to use open data. Adding facilitating conditions constructs to this model results in the same account of variability of behavioral intention to use open data ($R^2 = .429$ ($ps < .001$)). Adding facilitating conditions constructs shows that effort expectancy constructs ($p = .077$) and facilitating condition constructs ($p = .895$) become non-significant predictors of the variability of the behavioral intention to use open data. Compared to the original UTAUT model, we can conclude that our modified model performs slightly better than the original UTAUT model, as it accounts for 45.0% of the variability of the behavioral intention to use open data.

5. Recommendations

The research cohort of this study included researchers, citizens and civil servants mainly from the social science domain and already interested in the topic of open data. For this specific cohort of people, our research showed that various policy recommendations can be developed to improve their acceptance and use of open data technologies. In addition, this study provided directions for further research. These two types of recommendations are discussed in the following sections.

5.1. Recommendations for policy-makers

Our research showed that the UTAUT can be used to identify directions for open data policies that intend to increase open data use. Insight in how open data policies can be improved ultimately leads to achieving the high-level benefits of open data, including transparency, innovation and citizen participation. It was shown that the behavioral intention to use and accept open data technologies was significantly influenced by performance expectancy, social influence and effort expectancy. Based on the findings from this study, we developed the following recommendations for policy-makers to improve the use and acceptance of open data technologies.

5.1.1. Increasing the open data benefit awareness and expectations

In our study we found that the expectancy of open data users to perform better with open data technologies had the highest influence on the behavioral intention to use open data technologies. In a practical sense, this finding may direct policy and decision-makers towards taking initiatives that increase performance expectancy. The results of this study indicate that governments should mainly focus on creating more awareness of what can be done with open data technologies and which benefits can be obtained by them. Governments can improve the use of open data technologies by increasing people's expectations that such technologies will benefit them by helping them to accomplish their tasks more quickly, increasing their productivity and improving their job performance. Specific training programs focused on different types of end-users with various data use skills can be developed to maximize open data technology uptake. Workshops can be organized to disseminate training materials and to give training to (potential) open data users. Additionally, open data infrastructures may provide a learning environment to support end-users through demos, open online courses and audio visual examples on how open data technologies can be used. Such a learning environment may incorporate data use support elements such as a FAQ and a helpdesk. Training programs and learning environments are expected to empower users of open data technologies, which may lead to increased expectancy of the performance of open data users, and subsequently to a higher intention to use open data technologies.

5.1.2. Social media, networks and social strategies to encourage open data use

Social influence appeared to be important to improve the behavioral intention to use open data technologies. Practically, this suggests that the use and acceptance of open data technologies can be improved by convincing colleagues, family, friends, and other people who are important in the social circle of a potential open data user that open data should be used. Not having a portal, but building a user community and retaining this community is the key concern from this view. Governments could focus on social strategies to encourage people to use open data technologies. This finding shows that open data acceptance and use will not only be increased by improving open data technologies, but that social factors are also of significant importance. These results indicate that the adoption of a socio-technical perspective is more beneficial to increase open data use and acceptance than merely taking either a technical or a social perspective. Examples of social strategies that can be used to increase the intention to use open data technologies include the promotion and clear communication about open datasets to potential open data users, and the sharing of data use experiences by open data users. Viral social media strategies can be used to show the colleagues, family and friends of persons how they used open datasets. For instance, success stories and visualizations can be shared. Various visualization tools (e.g. Many Eyes, Google Developers) allow for sharing data visualizations via social media, such as Twitter and Facebook, or on websites. By using social strategies open data providers can engage with open data users, and may convince people in their network to also use open data.

5.1.3. Integrate open data use in daily processes and activities

We found that the voluntariness of using open data technologies negatively influences open data technology use and acceptance. The more compulsory, required and demanded by supervisors the use of open data becomes, the more the behavioral intention to use open data technologies increases. Naturally governments cannot 'force' the public to use open data. However, open data use may become less voluntarily by making open data use part of daily activities of individuals and organizations. Influential persons can play an important role in this process. For instance, teachers may integrate open data use in their courses. Education programs can be used to teach students which tools and techniques they can use for open data processing. Company managers may also integrate open data use in the daily work processes, and profit from new insights that can be obtained by integrating open data with business data. Such strategies intend to positively influence open data technology acceptance and use.

5.1.4. Training, education and other strategies to decrease the open data effort expectancy

The fourth predictor of the behavioral intention to use open data technologies found in this study was effort expectancy. It demonstrates that an increase in effort for using open data results in a decrease of the acceptance and use of open data technologies. This study shows that governments should focus on taking away barriers for the use of open data technologies rather than focusing on the publication of the data. The effort to use open data technologies needs to be decreased, for example, by providing data in easily reusable formats and through user friendly interfaces to easily find the data. Strategies to reduce effort expectancy may also focus on training and education for potential users of open data technologies to reduce the effort to use open data technologies. Additionally, reducing the effort to use open data technologies requires putting the user central in open data policies. Open data technologies and the infrastructures on which they are offered need to be user-friendly, and increase the user experience as much as possible. Although we did not find support for the hypothesis that facilitating conditions directly positively influence the behavioral intention to use and accept open data technologies, they may indirectly

still have an influence on open data use. The effort expectancy of open data users might be influenced by facilitating conditions, such as training and user-friendly infrastructures. This shows the need for clearly defining potential facilitating conditions and conducting further research on this.

5.2. Recommendations for further research

Theoretical contributions in the field of open government data are scarce (Magalhaes, Roseira, & Manley, 2014). In particular, there is a lack of insight with regard to the appropriateness of using certain theories for open data, the benefit of taking these theoretical views, and the context within which the theories can be used to understand open data (Zuiderwijk, Helbig, Gil-García, & Janssen, 2014). Little is known about what predictors affect the acceptance and use of open data. This paper is one of the few addressing open data theory development. This research helped in gathering insight in whether UTAUT can be used to enhance theory development in the field of open data and which theoretical UTAUT predictors significantly influence open data acceptance and use and which do not. In this paper we empirically tested UTAUT in the field of open data by means of a questionnaire about open data technology acceptance and use. The statistical analysis provided reasonable empirical support for UTAUT. Our research showed that UTAUT can be used to obtain a better understanding of the acceptance and use of open data technologies. We recommend further research in the following areas to increase the explained variability of open data technology acceptance and use.

5.2.1. Taking the context of open data into account

Some scholars have argued that UTAUT on itself cannot clearly define successful technology acceptance (e.g., Lancelot Miltgen et al., 2013). Venkatesh et al. (2003) found that the UTAUT explains about 70% of the variance in the behavioral intention to use a system or technology, whereas other models explain approximately 40% of the variance. Our model explained 45% of the variance, although we were not able to integrate the moderating variables into the model. Even though this is slightly better than the 40% explained by other models than UTAUT, it is still far from 70%. This means that a large part of the variance in the use of open data technologies is not yet explained. Although UTAUT was helpful, this theory has not been developed for open data in particular. More specific adoption theories need to take account of the context and specific conditions (Orlikowski, 2000), instead of black boxing Information Technology. Adoption theories for open data specifically are needed. There is a need for open data specific theories and methodologies that address the idiosyncratic nature of open data, including aspects such as data quality, institutional complexity, legal and economic aspects, citizens' needs, interoperability. For instance, the adoption of open data of low quality may differ considerably from the adoption of high quality open data. We recommend that adoption theories specifically for open data are developed.

5.2.2. Examining social network, disconfirmation and satisfaction constructs

Open data acceptance and use concerns human behavior, which is often difficult to predict. Future research should focus on how a model to predict open data technology use can be improved. Open data users want to use open datasets as a means to answer their questions, and they are mainly interested in the results from data analysis and reuse. Yet, politicians and existing benchmarks for evaluating open data adoption are often more focused on the supply of the datasets themselves rather than the use of datasets and its outcomes. For instance, research of Susha, Zuiderwijk, Janssen, and Grönlund (2015) showed that benchmarks for open data adoption often incorporate limited measures for data use and demand, while the provision of open data receives more attention in the measurements. More attention for constructs related to open data use and demand instead of open data provision is critical to explain open data adoption. Further research should examine the

extent to which open data use constructs play a role in the acceptance and use of open data technologies.

Several scholars have given suggestions about how to improve technology acceptance and use models. For instance, Sykes et al. (2009) have shown that it is important to take social network constructs into account when investigating system use in addition to the individual level constructs of UTAUT. They refer to the importance of network density (i.e. the network connectedness of a person to obtain help) and network centrality (i.e. a person's involvement in providing help to others). The networks of open data users may support open data use and may assist them in answering their questions. This shows the need to obtain more insight in the density and centrality of open data networks, so that social influence may be increased, and consequently the intention to use open data technologies may be increased.

Furthermore, Juell-Skielse, Hjalmarsson, Johannesson, and Rudmark (2014) identified factors that are important for participation in open data innovation contests. They state that important intrinsic motivations to participate in open data innovation contests are fun and enjoyment, intellectual challenge and status and reputation. An extrinsic motivation for open data users to participate in the collaborative production of digital open data services was user need. Although our study did not focus on open data innovation, factors such as fun, enjoyment and status may also be important for the use of open data technologies by researchers, citizens and civil servants. Factors related to fun, enjoyment, curiosity and learning were not included in our model concerning the use and acceptance of open data technologies.

Moreover, Bhattacharjee and Premkumar (2004) propose to integrate disconfirmation and satisfaction into future process models of long-run IT usage. Since our study was not longitudinal, it was only possible to evaluate open data usage at one moment in time. Venkatesh et al. (2011) added disconfirmation as a sub-variable for the UTAUT variables (e.g. disconfirmation of perceived usefulness and disconfirmation of effort expectancy) and by adding satisfaction as a separate variable. In addition, they articulate that the context should be taken into account and that trust should be included in the model (Venkatesh et al., 2011). These studies demonstrated that various beliefs can improve our understanding of the post-acceptance and use phase. More research on the acceptance and use of open data technologies could provide better insight in how open data use can be stimulated, and this will move the field forward.

In accordance with previous research (e.g., Rana et al., 2011), our study showed that facilitating conditions did not have a significant influence on the behavioral intention to use and accept open data technologies. It may have been the case that the facilitating conditions, such as the availability of a well-working internet connection, the assistance of a person or group for difficulties with open data use, and other resources, were relatively equal among the respondents. Another possible explanation for this finding could be that respondents did not know exactly what was meant with the term facilitating conditions, since this term was not specifically defined. Future research needs to investigate this.

5.2.3. Dealing with the diversity of open data perspectives

The field of open data is diverse and can be examined from a variety of perspectives, such as an economic, social, technical, institutional, operational, political and legal perspective (Zuiderwijk et al., 2014). A number of respondents stated that they did not have enough experience with the use of open data technologies to answer the questionnaire completely. Additionally, participants of this study were not asked from which country they came. Therefore, we could not investigate whether the variety in their answers to other questions was to a certain extent related to their country or a certain culture or to differences in countries' policies and efforts of open data use.

Moreover, this research was targeted at a specific group of people, namely researchers, citizens and civil servants from the social science

discipline who already showed interest in the field of open data. This study focused on the use of open data technologies for the purpose of research, scrutinizing data and obtaining new insights. The respondents mainly used open data to perform statistical analyses, to combine and integrate datasets, to write academic publications and to perform policy research. The respondents of our survey may have used open data technologies in a particular way that does not represent open data technology use by other stakeholders, such as entrepreneurs and developers. We expect that the respondents especially used open data technologies for their studies, and probably not for the development of products and services or to innovate in other ways. We recommend future research to examine the use of open data technologies for different types of users.

To examine the use of open data technologies by other types of open data users than the ones we studied, some variables of our model may need to be adapted. For example, the performance expectancy of developers may be different from the performance expectancy of researchers, since they may use different open data platforms, software, tools and interfaces. The effort expectancy may also differ, since obtaining data and data use technologies for research purposes may be easier than obtaining data for commercial open data use. According to their license, various datasets cannot be reused in a commercial way. In addition, the social environment of a researcher, citizen, civil servant, entrepreneur and developer is expected to be different and may influence the behavioral intention to use and accept open data technologies. Furthermore, facilitating conditions can be different for different types of open data users and different types of data technology use. For example, users' networks and the availability of appropriate open data infrastructures may differ, also for different types of data. Finally, whereas entrepreneurs and developers may use open data as part of their jobs and therefore in a less voluntary way than, for instance, citizens and civil servants, this might have biased the results of our study. This limits the representativeness of our research for the complete open data community.

We recommend that research on the acceptance and use of open data clearly defines from which perspective open data is investigated, rather than examining Information Technology adoption and open data as a uniform area. Future research on open data adoption can also be specific to a certain domain, such as geographical open data or social open data. Furthermore, since the use of open data technologies may differ per country and culture, we suggest that future research investigates to which extent the findings from this study are valid in individual countries, and for other cohorts of persons from the open data community. Additionally, differences in adoption per country might be traced back to a specific situation, such as public policies, features of open data portals and so on. This can provide insight in factors which influence the adoption of open data.

5.2.4. Intension or actual open data use?

This study focused on the relationship between five factors and behavioral intention to use open data technologies. According to the UTAUT model, behavioral intention is hypothesized to influence actual use behavior (Venkatesh et al., 2003). A limitation is that we did not study how the behavioral intention to use open data technologies is related to the actual use of such technologies. Johnson, Zheng, and Padman (2014) argue that measuring actual system use is problematic, since actual usage of a technology can be difficult to define and this type of information is often not available to researchers. However, several theoretical models have suggested that behavioral intention is a predictor of human behavior (Lee & Rao, 2009). Future research efforts should provide more insight in this regard in relationship to open data technology.

5.2.5. Open data technology use versus open data use

Finally, this study focused on open data technologies rather than on open data in general. There is a complex relationship between both, as

technology is needed to be able to use open data and open data use influences technology. The usage process can consist of various steps and often requires the discovery, scrutinization, processing, visualization and evaluation of open data using technology. Since we were interested in technology in this study, our study did not consider other aspects of open data use such as the capabilities and skills of the open data user, the quality of the data, the types of open data provided which might all play an important role. In addition to examining the use of open data technologies, we recommend future research to examine other aspects of the use of open data, including the influence of social aspects such as data use processes and user skills and a more fine-grained study as different types of data might require different processes and skills.

6. Conclusions

Governments expect that open data technologies will be accepted and used and that this will result in benefits ranging from transparency to economic development. Yet, mixed results can be found with regard to the acceptance and use of open data technologies. The objective of this study was to obtain more insight in the predictors of open data technology acceptance and use by applying the Unified Theory of Acceptance and Use of Technology (UTAUT). The original UTAUT model was modified by changing *Voluntariness of Use* into a direct predictor instead of a moderating variable. The study demonstrated that the direct predictors of the modified UTAUT model account for 45.0% of the variability of the behavioral intention to use open data, compared to 42.9% of the variability of the behavioral intention to use open data accounted for by the original UTAUT model. The intention to use open data appeared to be influenced by *performance expectancy* ($p < .001$), *social influence* ($p < .001$), *effort expectancy* ($p < .005$) and *voluntariness of use* ($p < .005$). In line with previous research, we found that one variable in our model did not significantly influence the intention to use open data, namely the *facilitating conditions* ($p > .005$). Social influence and performance expectancy are positively related, whereas effort expectancy is negatively related to the behavioral intention to use and accept open data technologies. The more voluntary the use of open data is, the lower the intention is to use open data.

The contributions of this study are both theoretical and practical. The practical contributions of this study lie in the analysis of predictors of the acceptance and use of open data technologies. Four key recommendations for improving open data policies were developed, namely 1) increase the performance with open data by generating more awareness of what can be done with open data technologies and which benefits can be obtained, 2) use social media, network and social strategies to encourage people to use open data technologies, 3) make open data use less voluntarily by making open data use part of daily activities of individuals and organizations, and 4) decrease the effort expectancy required to use open data technologies through training, education and other activities. Our analysis can be used to improve policies which aim to stimulate the use of open data technologies.

Moreover, this paper is one of the few contributing to theory development in the field of open data, and contributed to knowledge about predictors that are important in the field of open data technologies. We recommend future research on open data adoption 1) to take the context of open data better into account and compare different settings with each other and their effect on adoption, 2) to investigate additional constructs related to social networks, disconfirmation and satisfaction, suggesting to focus on open data communities rather than portals, 3) to take into account the diversity of open data perspectives and focus research on one area, 4) to examine to which extent the intention to use open data technologies influences actual open data use, and 5) to investigate the adoption of open data use in general in addition to the use of open data technologies.

Appendix A

Table 1

Overview of research constructs that were used in the questionnaire.

UTAUT construct	Questionnaire item (statement or question)	Type of outcome
Performance expectancy (PE)	Using open public sector data is of benefit to me (PE1)	Five-point Likert scale (strongly disagree–strongly agree)
	Using open public sector data will enable me to accomplish my research more quickly (PE2)	Five-point Likert scale (strongly disagree–strongly agree)
	Using open public sector data will increase my productivity (PE3)	Five-point Likert scale (strongly disagree–strongly agree)
	Using open public sector data improves my performance in my job (PE4)	Five-point Likert scale (strongly disagree–strongly agree)
Effort expectancy (EE)	It will be easy for me to become skillful at using open public sector data (EE1)	Five-point Likert scale (strongly disagree–strongly agree)
	Learning to use open public sector data will be easy for me (EE2)	Five-point Likert scale (strongly disagree–strongly agree)
	I clearly understand how to use open public sector data (EE3)	Five-point Likert scale (strongly disagree–strongly agree)
	I do not have difficulty in explaining why using open public sector data may be beneficial (EE4)	Five-point Likert scale (strongly disagree–strongly agree)
Social influence (SI)	People who influence my behavior think that I should use open public sector data (SI1)	Five-point Likert scale (strongly disagree–strongly agree)
	People who are important to me (e.g. family, friends) think that I should use open public sector data (SI2)	Five-point Likert scale (strongly disagree–strongly agree)
	People who are important to me (e.g. colleagues) think that I should use open public sector data (SI3)	Five-point Likert scale (strongly disagree–strongly agree)
Facilitating conditions (FC)	I have the resources necessary to use open public sector data (FC1)	Five-point Likert scale (strongly disagree–strongly agree)
	Open public sector data is compatible with other systems that I use (FC2)	Five-point Likert scale (strongly disagree–strongly agree)
	A specific person or group is available for assistance with difficulties concerning the use of open public sector data (FC3)	Five-point Likert scale (strongly disagree–strongly agree)
Behavioral intention (BI)	I intend to use open public sector data in the future (BI1)	Five-point Likert scale (strongly disagree–strongly agree)
	I predict that I will use open public sector data in the future (BI2)	Five-point Likert scale (strongly disagree–strongly agree)
	I plan to use open public sector data in the future (BI3)	Five-point Likert scale (strongly disagree–strongly agree)
Voluntariness of use (VU)	Although it might be helpful, using open public sector data is certainly not compulsory for my research or other activities (VU1)	Five-point Likert scale (strongly disagree–strongly agree)
	My research and other activities do not require me to use open public sector data (VU2)	Five-point Likert scale (strongly disagree–strongly agree)
	My superiors expect me to use open public sector data (VU3) (R)	Five-point Likert scale (strongly disagree–strongly agree)
	My use of open public sector data is voluntary (it is not required by my superiors/research/other activities) (VU4)	Five-point Likert scale (strongly disagree–strongly agree)
Gender (G)	Are you male or female? (G)	Multiple choice (male or female)
Age (A)	What is your age? (A)	Eight-point scale (under 18–61 or over)
Purpose of use (P)	To what extent are the following purposes important for your use of open public sector data? (P)	Five-point Likert scale (very unimportant–very important)
Type of data (T)	Which of the following types of open data from the public sector do you use or have you used? (T)	Multiple choice (type of public sector data: geographic, legal, meteorological, social, transport, business, other, namely ...)

Each statement or question was given a code, referring to the UTAUT construct. The items labeled “(R)” are reverse-coded.

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