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Kleiman, Fernando; Jansen, Sylvia J.T.; Meijer, Sebastiaan; Janssen, Marijn

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Understanding civil servants' intentions to open data: factors influencing behavior to disclose data

Fernando Kleiman
Faculty of Technology, Policy and Management, Delft University of Technology, Delft, The Netherlands
Sylvia J.T. Jansen
OTB Research Institute for the Built Environment, Delft University of Technology, Delft, The Netherlands
Sebastiaan Meijer
Department of Biomedical Engineering and Health Systems, KTH Royal Institute of Technology, Stockholm, Sweden, and
Marijn Janssen
Faculty of Technology, Policy and Management, Delft University of Technology, Delft, The Netherlands

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Abstract

Purpose – The opening of government data is high on the policy agenda of governments worldwide. However, data release faces barriers due to limited support of civil servants, whereas the literature neglects civil servants' role in opening data. This paper aims at understanding why civil servants can be reluctant to support the disclosure of data. The authors developed a model to explain civil servants' behavioral intention to open data.

Design/methodology/approach – The authors test a series of hypotheses by collecting and analyzing survey data from 387 civil servants and by applying multivariate hierarchical regression.

Findings – The results indicate the factors influencing the behavior of civil servants. Social influences, performance expectancy, data management knowledge and risks have a significant influence. Personal characteristics control these effects.

Research limitations/implications – Caution is needed to generalize the findings towards the support to open data provision by civil servants. Though the analyzed sample was limited to Brazil, other countries and cultures might yield different outcomes. Larger and more diversified samples might indicate significant effects on variables not found in this research.

Practical implications – The insights can be used to develop policies for increasing the support of civil servants towards governmental data disclosure.

Originality/value – This study suggests factors of influence to civil servants' behavior intentions to disclose governmental data. It results in a model of factors, specifically for their behavioral intention at the individual level.

Keywords Open data, Open government, Behavior, Barriers, Adoption, Attitude, Learning

Paper type Research paper

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1. Introduction

The opening of data by governments is high on the political agenda in many countries to increase transparency, participation and innovation (Fermoso *et al.*, 2015; McDermott, 2010; Zuiderwijk *et al.*, 2018). Open data relates to any data produced by any device or person, which is publicly shared for free or at a minimal cost, and that can be accessed by anyone. There are many benefits resulting from governments disclosing data, such as greater transparency, accountability, anti-corruption actions, trust, increased participation and for improving and generating new economic activities (Davies *et al.*, 2019; Janssen *et al.*, 2012; Safarov *et al.*, 2017). These benefits also converge with the increasing interest for research focused on the role of governments in strengthening democracy.

Many countries are already achieving some of the benefits coming from open data (Herala, 2018; WorldBank, 2014). However, a large number of datasets are still not open. Reasons for the low opening of data include infrastructural limits to digitalization and communication technologies, a lack of skilled personnel (Davies *et al.*, 2019; Fermoso *et al.*, 2015; Ubaldi, 2013) and risk-averse behavior (Buurman *et al.*, 2012). Those countries that established standardized infrastructures for the opening of data (Davies and Calderon, 2020) now shift the emphasis to civil servants to open up more data.

In the decision process to opening data, typically, several civil servants are involved. Civil servants are the professionals that operate governmental policies, and can be related in different aspects of governmental data disclosure (Lipsky, 1971; Lotta and Marques, 2019). They are the bureaucrats who create the datasets, evaluate the potential of opening these datasets, and decide whether to open or not and do the actual opening. Usually, decision-making to open a dataset is not left to a single person but involves multiple civil servants (Denis and Goeta, 2017). Each civil servant can take different concerns into account, such as privacy, sensitivity and societal benefits.

However, the diversity of civil servants complicates decision-making, as some of them may oppose due to their focus on possible risks and lack of prior experience to assess the impact of these risks. Although guided by policies, civil servants have the discretionary power to influence decisions based on their in-depth knowledge of the situation at hand. In contrast to politicians, civil servants are more permanent in government and act based on their risk-avoiding routines, background information and legislation allowing specific actions (Lipsky, 1971; Lotta and Marques, 2019; Stoffregen *et al.*, 2015). There are trade-offs faced by civil servants, such as having an increase in work hours for having to select data to be opened, while there can be a decrease in workload afterward, for having to handle less information requests once open data has been made available (Denis and Goeta, 2017; Janssen *et al.*, 2012). A dataset's content can contain private or sensitive information, which can also influence their willingness to support the data opening (Ruijer and Meijer, 2019).

Civil servants operating the government can foster or limit the opening of data. Some might adhere more to the idea of opening data, whereas others might have a risk-averse attitude to avoid any claims at a later stage. A study among municipalities shows that different local governments had divergent responses to disclose similar data, suggesting some level of arbitrariness in the opening of data based on freedom of information (FoI) requests (Kuk *et al.*, 2017), and that the civil servants' behavior to open data is crucial. In this research, our aim was to sample a diverse set of civil servants within governments ranging from street-level bureaucrats, to top-level decision-makers and advisors.

Open data is a vibrant field, and many aspects have already been researched (OECD, 2018; Sieber and Johnson, 2015). Previous research focused on users' adoption (Attard *et al.*, 2015; Zuiderwijk and Cligge, 2016; Zuiderwijk and Hinnant, 2019; Zuiderwijk and Janssen, 2014), and challenges to get public personnel to support data opening (Safarov *et al.*, 2017; Wirtz *et al.*, 2016). However, few studies focus on the behavior of civil servants.

Civil servants' knowledge, risks-aversion, culture and many other factors can play a role in shaping such behaviors (Conradie and Choenni, 2014; Crusoe and Melin, 2018; Janssen *et al.*, 2012). As behavior is challenging to measure and observe, behavior intention is often used as a predictor (Ajzen, 1989; Madden *et al.*, 2016). Therefore, in this paper, we develop a model to understand what influences the behavioral intention of civil servants to support the opening of governmental data. To our knowledge this is the first model focused on understanding and explaining factors influencing behavior intention. Hence, this study takes a different approach than previous studies that focused on open data adoption by users. Moreover, our focus is on civil servants and not on open data users, which is the main focus of most research. Furthermore, our work also contributes to the discussions to let governments open more data, taking the providers' perspective.

We took the theoretical discussion from the literature, and we progressed by collecting survey data. Although our initial aim was to have representation from many countries, we were only able to collect data in Brazil due to our close relationship with the government. Brazil has occupied an outstanding position in terms of national policies fostering open data in the last decade, and was selected as a target sample for testing our hypothesis (Ruediger and Mazzotte, 2018). Brazil has a diverse population representing various cultures contributing to the generalization of the findings to other countries. According to the Open Data Barometer, which is a common reference to assess countries' performances on open data (Wang and Shepherd, 2020), Brazil is the second-largest country, ranking within the top 20 countries in the world. Furthermore, as limited attention has been given to developing countries in the literature (Safarov *et al.*, 2017), collecting data in Brazil contributed by collecting data in developing countries.

In the next section, we discuss Behavioral Intention and develop seven hypotheses of main factors influencing civil servants' behavior. Furthermore, a hypothesis on the controlling effects of personal characteristics is developed. In section 3, the research approach is presented, explaining the data collection and the analysis. The results are presented in section 4. Sections 5 and 6 presents the discussions and conclusions resulting from this research.

2. Background – research hypothesis

This paper aims at exploring the factors which can influence civil servants' attitudes towards open data provision by governments. Our main research question is:

RQ1. Which factors can influence civil servants' behavior intention (BI) to support the opening of data by governments?

In this section, the BI is explained, and the seven factors hypothesized to influence civil servants' behavior are discussed. Besides, the personal characteristics' controlling effects are hypothesized. The results of the hypotheses testing are presented in Section 4.4 based on the collected data and discussed throughout our discussion and results.

2.1 Behavioral intention

Civil servants' behavior can only be measured indirectly. According to Davis (1989), BI can be seen as a measure of one's future intention to perform a specific behavior. Hence, BI can be used as a proxy to estimate an individual's support for certain actions, which is in our research, the intention to open governmental data. Technology acceptance models (TAM, TAM2 TAM3 and Unified theory of acceptance and use of technology (UTAUT) (Venkatesh and Davis, 2000) and other adoption models (DeLone and McLean, 1992), use BI as a compound variable. The effects of other factors at the individual level are included in this compound variable, such as the adoption of technology or predictions of its use (Ameen *et al.*, 2020; Cigdem and Topcu, 2015). BI is defined in this research *as civil servants' willingness to support the opening of data.*

As a proxy for measuring behavior, the willingness of civil servants to support the opening of data is measured by using three items (see Appendix for full references). The first, more practical, is to assess whether these professionals are already providing governmental data to the public and if they are aware of doing so. A second item is their declared disposition to do so. The last item is the prediction of needing to disclose data in the future. This item captures the vision of how open data practices are going to be adopted in the future of public service. The compound variable of BI is assumed as one construct resulting from these three items (all the items are described in Appendix). In the next subsection, we present the influence factors of BI, to be developed and tested as the aim of this research.

2.2 Hypothesizing factors influencing behavioral intention

Whereas there is extensive literature about BI (Ajzen, 1991; Bandura, 1986; Cigdem and Topcu, 2015), there is a void in research about the behavior intentions to open data (Jurisch *et al.*, 2015). Some studies developed tentative approaches, but these works are focused on user adoption and not on providers of open data (Weerakkody *et al.*, 2017; Zuiderwijk *et al.*, 2015). The latter is the focus of our research. Consequently, limited related work was available as a basis, and our work contributes to theorizing.

2.2.1 Performance expectancy. In our model, performance expectancy (PE) summarizes all the positive outcomes of releasing governmental data, including its benefits for the civil servants individually, and social values. The more civil servants can perceive the benefits that might result from data opening, the more likely it is that they support data disclosure (Kleiman *et al.*, 2020b; Zuiderwijk *et al.*, 2018). PE is based on Venkatesh *et al.* (2003) and is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447). We expand this definition to include societal benefits, which is commonly used in perceived usefulness at the organizational level, but we translated this to the individual level (Weerakkody *et al.*, 2017; Wirtz and Piehler, 2016; Wirtz *et al.*, 2016). The assessment of the perception of these benefits is performed at the individual level (Kalampokis *et al.*, 2011; Schnake and Dumler, 2003) since the goal of this measurement is to study its influence on a person's BI. As we expect that the more benefits civil servants' expect from opening up data, the more they will support its release, our first research hypothesis is:

H1. PE will positively influence the BI of civil servants to support open data.

2.2.2 Social influence and risks. Whereas the previous factor focuses on the positive aspects, there are also factors influencing the behavior of open data negatively. In the literature, there are two groups of barriers originating from the social or risk perceptions of open data related to the environment and culture of governments.

The first group includes the social influences of public administration itself, such as fears related to legal frameworks and hierarchy (Kleiman *et al.*, 2020a, b; Pasquier and Villeneuve, 2007; Schepers and Wetzels, 2007). Wirtz *et al.* (2016) and H.-J. Wang and Lo (2016) used bureaucratic decision and hierarchical barriers, which is included in Social Influence. In addition, Janssen *et al.* (2012) found that a lack of support to make data available, the threat of lawsuits or other violations, such as privacy or security at the organizational level, might lead civil servants to resist to open data.

H2. Social Influence (SI) will negatively influence the BI of civil servants to support open data.

The second group of barriers refers to the perceptions of the organizational and political risk involved in sharing governmental data (Bélanger and Carter, 2008; Carter and Bélanger, 2005; Schaupp and Carter, 2010). Also, Ruijer and Meijer (2019) indicated the existence of cultural barriers to open data, such as fear of misinterpretations or data abuse. These barriers are grouped into the RK construct that is hypothesized as follows:

H3. RK will negatively influence the BI of civil servants to support open data.

2.2.3 Data management knowledge. Another group of factors that can influence civil servants' perception of open data negatively is their data management knowledge (Hossain *et al.*, 2016; Janssen *et al.*, 2012). As found by Denis and Goeta (2017): "In administrations, the important thing regarding data, our interlocutors told us, is that most people do not know they work with such things as 'data'" (p.609). A lack of knowledge about what constitutes data and how to manage it impacts the understanding of the operations and routines related to the release of data (Crusoe and Melin, 2018, de Juana-Espinosa and Luján-Mora, 2019; Ruijer and Meijer, 2019). Having knowledge will make it easier to support the opening of data.

H4. Data Management Knowledge (DK) will positively influence the BI of civil servants to support open data.

Three other variables related to the knowledge of public data management are tested in terms of influence in the behavior intention of civil servants (Conradie and Choenni, 2014; Hossain *et al.*, 2016; Janssen *et al.*, 2012). We assessed if civil servants realize that their work produces data and that these data can be opened. They might simply not recognize that they produce data that might be valuable for the public. Many everyday activities might seem unimportant, and the resulting data might not be recognized as having the potential to be opened or being valuable for others.

H5. Knowledge of data production (DP) will influence the BI of civil servants to support open data.

Moreover, some of the data produced are stored locally, and civil servants do not come up with the idea to share this data with a broader public (Conradie and Choenni, 2014). They might not be aware of the possibilities to release their data and the infrastructure and support offered (Crusoe and Melin, 2018; Hossain *et al.*, 2016). Realizing the availability of sharing data as an option is crucial for them to consider opening.

H6. Knowledge of data sharing (DS) as a possibility will influence the BI of civil servants to support open data.

Finally, the perception of costs needed to share data can also influence their disposition to make the data public. Denis and Goeta (2017) indicated that "data labour is acknowledged as a crucial part of the opening process, the cost of which represents an investment. This implies the creation of new positions and the redefinition of some others within the organization" (p.619). Opening processes also need people executing them.

Costs might be perceived not only in terms of budget but also the time needed to process data for opening. Civil servants might simply feel that they lack this time to open data (Conradie and Choenni, 2014; Crusoe and Melin, 2018; Denis and Goeta, 2017). They might also believe that costly hardware and software are needed to make data opened. In that sense, the opening of data might be viewed as too expensive. We consider this as the fourth dimension of knowledge, which is hypothesized as:

H7. The perception of costs (DC) for data provision will negatively influence the BI of civil servants to support open data.

2.3 Hypothesizing effects of personal characteristics

Personal characteristics of the individual civil servants can also have a direct and indirect role in their willingness to support the opening of data. Following DeSmet *et al.* (2018), characteristics such as age, gender and previous experiences in the public sector and with open data were included in the model. Besides, the different governmental level, positions and roles of civil servants was analyzed towards differentiating their relation to open data. These traits were tested in a block to distinguish their explanatory power from the power of the model factors, through hierarchical regression analysis.

Personal Risk-Aversion (RA) can play a role when making decisions (Peled, 2011; Rehouma and Hofmann, 2018). For a more precise measurement, we use multiple items assessment with four questions included as one group within personal characteristics. RA assesses a general perception of the respondent related to personal attitudes in private life, such as sharing personal data through the Internet or being excited with unexpected situations. Risk-Aversion is assessed at the individual level and is different from the construct of Risks (RK), which includes the perceived negative consequences of open data for governmental organizations.

This group of personal characteristics can directly relate to their willingness to support the opening of data (Rehouma and Hofmann, 2018). We included them as a group, as, when left out of the analysis, they can have an indirect effect on the civil servants' BI through model factors with which they share a relationship. An example is that more experienced civil servants may have less expectancy on open data benefits; therefore, they may have a lower BI to support open data. These characteristics are clustered into a group and tested on the controlling effects of the analysis (Lewis, 2007).

H8. Personal characteristics of the respondents will not control the model factors' influence on the BI of civil servants to support open data.

3. Research method

This paper aims at developing and testing a model of factors influencing civil servants' intention to open governmental data. By taking a quantitative approach we contributed to the open data literature, which is majorly qualitative (Safarov *et al.*, 2017). The previous section discussed the literature and indicated factors to build up a model of influence on attitudes towards data provision. We based this discussion on papers (Kleiman *et al.*, 2020a; Kleiman *et al.*, 2020a, b) that, through systematic literature reviews (Kitchenham *et al.*, 2009), found many studies focused on open data, however just a few related specifically to civil servants and their behavior. These papers elaborated on factors which we translated into hypotheses and tested using the data collected through a survey targeting civil servants. An inductive, qualitative, approach (the literature review), was used to develop a theoretical model of the aspects that potentially could influence the intention to share open data. Next, a deductive quantitative approach (the online survey) was used to test the theoretical model (Saunders *et al.*, 2016). The systematic literature review was chosen because the literature provided multiple available studies that could be summarized in an overview of potential aspects that could influence the intention to share open data. Besides, it provided us with an understanding of the important theories, concepts and debates in this field of research (Saunders *et al.*, 2016). The online survey was chosen for various reasons. In order to be able to test the theoretical model a relatively large number of respondents was needed. An online survey is usually easy to administer and is relatively inexpensive (Sekaran and Bougie, 2016). It also provided us with the opportunity to reach a large number of respondents throughout the country.

We analyzed this data using regression analysis which is a widely used and accepted method of analyzing data to test the influence of predictors (Ameen *et al.*, 2020; Cuillier and Piotrowski, 2009; Schepers and Wetzels, 2007). As defined by Field (2009), regression analysis is "a way of predicting an outcome variable from one predictor variable (simple regression) or several predictor variables (multiple regression)" (p. 198).

We used a Backward elimination-by-hand procedure as our aim is to arrive at a parsimonious model. This means that nonstatistically significant predictors were excluded one at a time. First, the predictor with the highest nonstatistically significant *p*-value was removed from the model. Next, the model was rerun (without this predictor), and the predictor with the highest nonstatistically significant p-value was removed from the model. This procedure was repeated until only statistically significant predictors remained. The benefit of this procedure is that insight is gained into the way in which predictors relate to each other and the effect of removing one predictor on the performance of the whole model. Dummy variables reflecting a particular variable were either simultaneously removed or kept into the model.

We use multiple regression related to BI, including the variables which were established in the model, and tested them for personal traits' controlling effects, through a hierarchical regression. As defined by Lewis (2007), a hierarchical regression "can be useful for evaluating the contributions of predictors above and beyond previously entered predictors, as a means of statistical control, and for examining incremental validity" (p. 9). A block of items that are not part of a model's main variables such as age, gender or previous experiences with a certain subject is defined. This block of items is previously entered in the regression for controlling the contribution to the variance of the model predictor variables, which are entered later.

A survey was developed to test the hypotheses, as formulated in the previous section, consisting of 33 questions about influencing factors and another 14 questions about personal characteristics (see Appendix for all the items). In total, 387 civil servants completed the survey.

3.1 Data collection

A survey was distributed by email using a mailing list targeting civil servants by the Frente dos Prefeitos (one of the national association of municipalities from Brazil), the Municipality of São Paulo, the Management Secretariat in the Ministry of Economy, the UNU-eGov (United Nations University) and the WeGov Network. The survey was also shared by some civil servants on their personal social network profiles. Both online and on paper were the surveys distributed to gain as many responses as possible. The paper-based survey reached 92 civil servants from the Municipality of Sao Paulo and the Federal level, and another 463 were completed online on Qualtrics (digital survey website).

From 29 November 2019 until 5 April 2020 the survey was distributed, and 70% out of 555 (n = 387), who clicked on the link, completed the survey. As 168 respondents did not answer all questions, these were excluded from the analysis. The complete questionnaires resulted in the sample described in Table 1. The sample represents a population of the permanent staff of public service (69%) with 25–45 years old (58%) with at least 5 years of public service experience (80%) in which more than 40% are female. The sample represents a knowledgeable population, as 94% declared to have heard of open data before and 86% have been an open data user.

3.2 Measurement

All measurements were assessed through a 7-point Likert scale survey build upon previous literature references (Kleiman *et al.*, 2020a, b). Each of the items composing the constructs, and those tested individually, can be found in Appendix. The survey pilot-test was conducted with colleagues researchers. The BI construct is based on previous models of technology adoption models, specifically, those related to open data, when available (Chen *et al.*, 2017; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003; Weerakkody *et al.*, 2017; Wirtz and Piehler, 2016; Zuiderwijk *et al.*, 2015).

The items included in the construct of PE are based on previous literature (Davis, 1989; Moore and Benbasat, 1991; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003; Weerakkody *et al.*, 2017; Zuiderwijk *et al.*, 2015). SI items were derived from the literature on government and factors of influence (Moore and Benbasat, 1991; Weerakkody *et al.*, 2017; Wirtz and Piehler, 2016). The DK and RK construct items were developed using literature discussing how to measure adoptions in different organizational contexts (Chen *et al.*, 2017; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003; Zuiderwijk *et al.*, 2015).

Category	Values	Frequency	%
Gender	Male	221	57%
	Female	153	40%
	missing	13	3%
Age	Less than 25	21	5%
	26–35	93	24%
	36–45	133	34%
	46–55	72	19%
	Above 56	28	7%
	missing	40	10%
Government type/Level	Municipal	79	20%
	Federal	90	23%
	Other	204	53%
	missing	12	3%
Years of work in government	0 – 5 years	76	20%
	5+ –10 years	98	25%
	10+ –15 years	86	22%
	15+ –20 years	54	14%
	20 years+	59	15%
	missing	14	4%
Work contract	Politically appointed	69	18%
	Permanent staff	267	69%
	Hired	17	4%
	Other	25	6%
	missing	9	2%
Previous knowledge about open data	Heard of . . .	361	93%
	Studied . . .	278	72%
	Used . . .	334	86%
	Feel somehow comfortable to share own private data on the internet	150	39%
	Total (completed surveys)	387	100

Table 1.
Overview of demographics

4. Results

4.1 The internal reliability of the dependent variable and predictors

Each construct was measured using groups of the 33 survey items. The reliability of these constructs was checked using Cronbach's Alpha (Hof, 2012). The items with regard to BI ($\alpha = 0.800$, 3 items); PE ($\alpha = 0.734$, 10 items); SI ($\alpha = 0.742$, 9 items); RK ($\alpha = 0.669$, 5 items); and DK ($\alpha = 0.747$, 3 items) loaded satisfactorily on their constituting factors. As explained above, personal characteristics were added as predictors in the model. The items DP (I produce public sector data in my work), DS (some public sector data can be shared) and DC (the costs of providing public sector data are too high) did not load in any of the constructs and were treated individually. Finally, the variable DS was excluded from the analysis because of the high number of missing values (Field, 2009) that occurred due to an error in programming the digital questionnaire.

Information was collected about the personal characteristics: age, gender, personal risk-aversion, level of government, previous experience in the public sector and experience with open data, as presented in Table 1. The resulting model is presented in Figure 1.

4.2 Checking assumptions to run the regressions

The first step to run the regressions and explore the relations between the BI of civil servants and its influencing factors is to check the data and variables using frequency tables (Field, 2009). Before running the multivariate regression analyses related to BI, the bivariate relationships were explored to determine relationships between each predictor and the outcome using correlation (numerical measurement level) and the independent samples *t*-test for gender (Field, 2009) – Table 2 and Table 3.

The bivariate results show that PE, DK, SI and DP are statistically significantly and positively related to BI. Within the tested personal characteristics, Experience with Open Data, Experience in Public Sector (except EPS11), personal Risk Aversion (except RA12 and RA14) and gender shows statistically significant and positive relations to BI. EPS13 shows a negative relationship with BI.

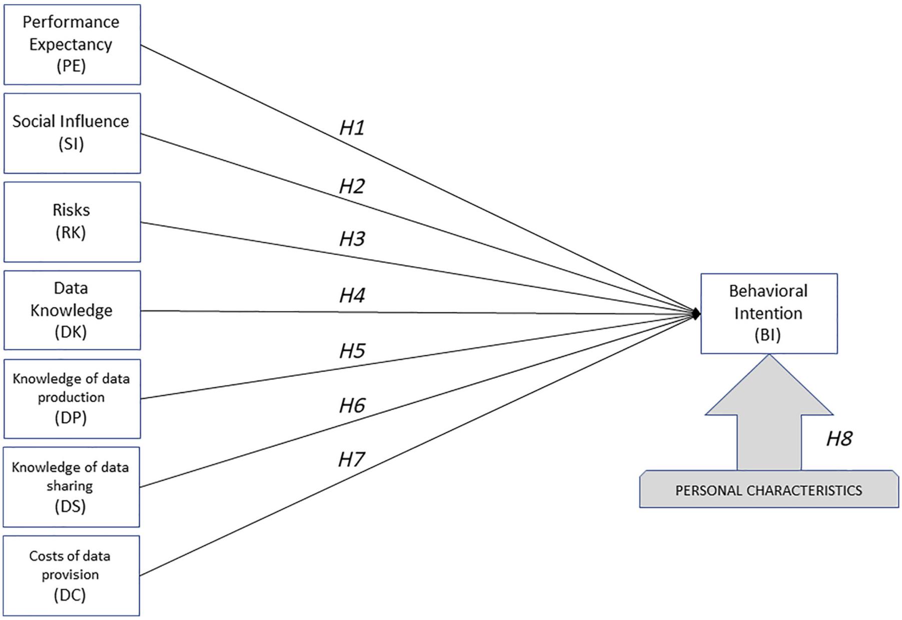

Figure 1.
Research model

Model factors	Pearson correlation	Sig. (1-Tailed)
Social influence	0.624	<0.01
Data management knowledge	0.433	<0.01
Performance expectancy	0.233	<0.01
Risks	−0.01	0.46
Knowledge of data production	0.37	<0.01
Costs of providing data	−0.04	0.24
Personal characteristics		
Experience with open data	0.34	<0.01
Personal risk aversion (relation to unexpected)	0.20	<0.01
RA_11 (intention to share personal)	0.16	<0.01
EPS_12 (function performed)	0.15	<0.01
EPS_13 (contractual relation)	−0.11	0.01
EPS_11 (years in public service)	0.06	0.12
Age	−0.01	0.42
RA_14 (professional stability importance)	−0.03	0.31
RA12 (going against the law)	−0.04	0.23

Table 2.
Pearson correlations (numerical variables to BI)

The correlations between the independent variables were analyzed to check for multicollinearity. The highest correlation occurred between PE and DK at 0.49. As the results did not show any correlations higher than 0.7, the regression analysis was performed without multicollinearity (Field, 2009).

4.3 Running the regression

The relationship between the BI of civil servants to support open data and the predictors (PE, RK, SI, DK, DP and DC to BI) was analyzed using multivariate regression analysis. This regression resulted in a first model that explained 45% of the variance in the BI ($F(6, 379) = 52.39, p < 0.01, R^2 = 0.453$). Only one outlier had a standardized residual greater than three, which turned out not to be an influential outlier (Cook's Distance lower than one). After manually checking the effects on the sample, this outlier was considered irrelevant for influencing the outcomes.

The results (standardized coefficients) show that SI is the most important predictor of BI. They indicate that with each unit increase in SI (measured with the use of a 7-point Likert scale), the BI increases by 0.72. The second most important predictor is PE, followed by knowledge of DP and DK – Table 4.

We tested each categorical variable's effects by using a set of dummy variables for each category (Gould-Williams, 2004; Grimmelikhuijsen and Feeney, 2017). We checked the outliers to verify any noise produced by strange records in the remaining dataset. The standardized residuals analyses resulted in only three cases, registering more than 3 standard deviations from the mean. After having checked these manually, we concluded that regular outliers have limited influence on the outcomes and were not made by mistake, so they were kept in the analysis. Next, a hierarchical regression analysis was performed in two steps. First, by including only the personal characteristics; and thereafter by also including the model predictors (PE, RI, SI, DK, DP and DC) (Baron and Kenny, 1986; Jansen *et al.*, 2017).

4.3.1 Results of personal characteristics. The regression analysis started including all personal characteristics in the first block and BI as the dependent variable. In total, 22 variables were included in the model, among them 14 dummies created for controlling the effects of 4 categorical variables (3 variables related to experience in public sector with 5 categories each, and the level of government with 3 categories) - ($F(21, 305) = 3{,}13, p < 0.001, R^2 = 0.18$). See Appendix for an overview of these variables.

Table 3.
Independent sample *t*-tests scores (nominal variables to BI)

	t	*df*	*p*
Gender	−2.478	372	0.01

Table 4.
Initial model coefficients

	Coefficients Unstandardized Beta	Standard Error	Standardized Beta	Significance
Constant	−0.29	0.58		0.86
Risks	−0.06	0.05	−0.05	0.19
Data management	0.14	0.05	0.12	<0.01
Performance expectancy	0.20	0.09	0.09	0.03
Social influence	0.72	0.07	0.49	<0.01
Knowledge of data production	0.17	0.04	0.19	<0.01
Costs of data release	−0.03	0.04	−0.03	0.404

A second step included RK, DK, PE, SI, DP and DC as predictors in the regression. Results of the multiple linear regression indicated that there was a significant collective effect between the predictors and BI, (F(27, 299) = 10.82, $p < 0.001$, $R^2 = 0.494$). Some individual predictors did not show statistical significance, which indicated that the model could be improved by their extraction (Field, 2009; Jansen *et al.*, 2017).

Age was removed from the model as it had a larger number of missing values. It was not a mandatory field and did not show a statistically significant bivariate relationship with BI. The resulting model has somewhat lower percentage of explained variance (F(26, 329) = 11.82, $p < 0.001$, $R^2 = 0.483$).

Using the manual Backward-elimination procedure the nonstatistically significant predictors were excluded from the model in the following order: Government type or level they work, Type of work contract, RA_11 (on their intention to share personal data on the Internet), gender, Experience in the Public Service (EPS)_13 (on their contractual relation to government), RA_14 (on professional stability importance) and RA12 (on going against the law).

Once more, the multiple linear regression resulted in a significant collective effect between the predictors and BI (F(12, 354) = 26.65, $p < 0.001$, $R^2 = 0.47$). Table 5 presents the coefficients and significance of the predictors and personal characteristics of the final model in comparison to the predictors of the initial model. In any scenario or step, SI is the most influencing variable with a coefficient of 0.72 ($t = 10.42$, $p < 0.01$). This is suggesting that government issues related to the legal framework and hierarchy impact civil servants' support for releasing governmental data. Furthermore, SI is not affected by the introduction of any controlling variable. Hence, civil servants' political and legal support results in important effects to increase the opening of data.

Only the personal characteristics of the participants explain 13.6% of the variance in BI. The ΔR^2 with the inclusion of SI, DK and DP is 0.33, meaning that the model increases the predicting power by 33.4% over the defined personal characteristics.

The outcomes suggest that the civil servants' perceptions of RK and DC did not significantly influence their BI. Within the personal characteristics, for public service experience only the duration which the civil servant has worked for the government resulted

Dependent variable: BI	Section 4.3 (Initial model) (F(5, 380) = 62,78, $p < 0.001$, $R2 = 0.452$)		Section 4.4 (Final model) (F(12, 354) = 26,65, $p < 0.001$, $R2 = 0.475$)	
Predictors	B	Sig	B	Sig
Risks	−0.06	0.25	−0.07	0.23
Data management knowledge	0.14	<0.01	0.09	0.08
Performance expectancy	0.20	0.03	0.11	0.25
Social influence	0.72	<0.01	0.72	<0.01
Knowledge of data production	0.17	<0.01	0.16	<0.01
Costs of data release	−0.03	0.404	−0.02	0.68
Personal characteristics				
Experience with open data	–	–	0.15	<0.01
Personal risk aversion (relation to unexpected)	–	–	0.07	0.06
Experience in public sector (5+ – 10 years)	–	–	0.48	<0.01
Experience in public sector (10+ – 15 years)	–	–	0.36	0.06
Experience in public sector (15+ – 20 years)	–	–	0.48	0.03
Experience in public sector (more than 20 years)	–	–	0.26	0.22

Table 5.
Controlling effects

in statically significant results. The type of contracts, level of work or job type did not result in any differences in predicting the intentions to open governmental data. The defined predictors of BI to share open data were not related to the level of their government (local, federal or other), the role they have in their governments (EPS_12), their easiness of sharing their own personal data on the Internet (RA11). Also, gender, the type of professional contract they have with the government (EPS13), the importance that professional stability has in their lives (RA_14), or the importance they give to respecting the law (RA12) were not found to be influential.

4.4 Testing the hypothesis

The results of the hypotheses testing for the fit of the resulting final model are shown in Table 6. The hypothesis testing shows that, H2, H3 and H5 are confirmed with and without the introduction of personal characteristics. SI and DP are the only factors indicating statistically significant relations with BI. By introducing the block of personal characteristics, the p-value from DK decreases from <0.01 to 0.08, which means that the factor is not statistically significant anymore. Moreover, the same applies to performance expectancy, which p-value reduced from 0.03 to 0.25 and is also not statistically significant after the personal characteristics' introduction. From another perspective, the indirect effect that the personal characteristics have on BI through PE and DK has corrected the model.

On the other hand, H1, H4 and H7 are not significant, suggesting that RK, and DC are not influential in defining civil servants' BIs. Unfortunately, as presented in Section 3.1, H6 could not be tested as it had a technical register problem resulting in no information on the DS for the present exercise.

The comparison between the model without and with the personal characteristics shows that personal characteristics (H8) do influence the model. These items control some of the original model predictors' effects. Three personal characteristics items (experience with open data, experience in public service and RA) changed the influences of the original model constructs. PE was the most affected construct, which statistical significance was reduced in the model with personal characteristics – Figure 2. Hence, the individual background traits, such as experiences, are likely to be influential to the expectancy of benefits that open data can produce.

5. Discussion

5.1 Main findings

This study aims to explain factors influencing civil servants' behavior intention to support the opening of data by governments. Data was collected using a survey and a regression analysis was performed in order to analyze the seven factors hypothesized to influence civil servants' BI to support open data. The influence of each of the factors is presented next to discuss the findings and explore its consequences.

The final model indicates that *DP* has a significant influence on BI, e.g. the item "I produce public sector data in my work" ($t = 4.46$, $p < 0.01$). The findings suggest that civil servants should be educated and trained in releasing public data and being made aware that they might produce data that can be opened. As found in Denis and Goeta (2017), understanding the basic operations and dynamics needed to publish data can change civil servants' perceptions. Many professionals might not realize that they generate data that can potentially be disclosed. Correspondence, reports, registers or other communications can be opened as it might be interesting for the public for all kinds of reasons. Raising awareness of DP in governments should produce considerable results, even with a highly educated sample that declared to know about data policies, as 72% of the respondents declared to have studied open data, as shown in Table 1.

Hypothesis	Result	*P*-value
H1: Civil servants' Behavioral Intention to support governmental data disclosure will be positively influenced by Performance Expectancy (PE)	Not significant (accept the null hypothesis)	0.25
H2: Civil servants' Behavioral Intention to support governmental data disclosure will be negatively influenced by Social Influence (SI)	Significant (reject the null hypothesis)	*<0.01*
H3: Civil servants' Behavioral Intention to support governmental data disclosure will be negatively influenced by Risks (RK)	Not significant (accept the null hypothesis)	0.23
H4: Civil servants' Behavioral Intention to support governmental data disclosure will be positively influenced by Data Management Knowledge (DK)	Significant (reject the null hypothesis)	*0.08*
H5: Civil servants' Behavioral Intention to support governmental data disclosure will be influenced by Knowledge of data production (DP)	Significant (reject the null hypothesis)	*<0.01*
H6: Civil servants' Behavioral Intention to support governmental data disclosure will be influenced by Knowledge of data sharing (DS)		Excluded from the testing for having too many missing cases
H7: Civil servants' Behavioral Intention to support governmental data disclosure will be negatively influenced by the perception of costs (DC) for data provision	Not significant (accept the null hypothesis)	0.68
H8: The model factors' influences on the Behavioral Intention of civil servants to support open data will not be controlled by personal characteristics of the respondents	Significant for aspects (reject the null hypothesis)	Experience in Public Service (years) *p= <0.01, p = 0.06, p = 0.03* and *p* = 0.22 respectively to categories "5+ to 10", "10+ to 15", "15+ to 20" and "20+" in relation to "0 to 5" Previous Experience with Open Data *p* = <0.01 Personal Risk-Aversion *p* = 0.06

Note(s): Italics = Statistically significant results

Table 6. Results of the hypothesis testing

The relationship between DK and BI was affected by personal characteristics, having the influence of DK lowered and turned into a *non*statically significant predictor after the

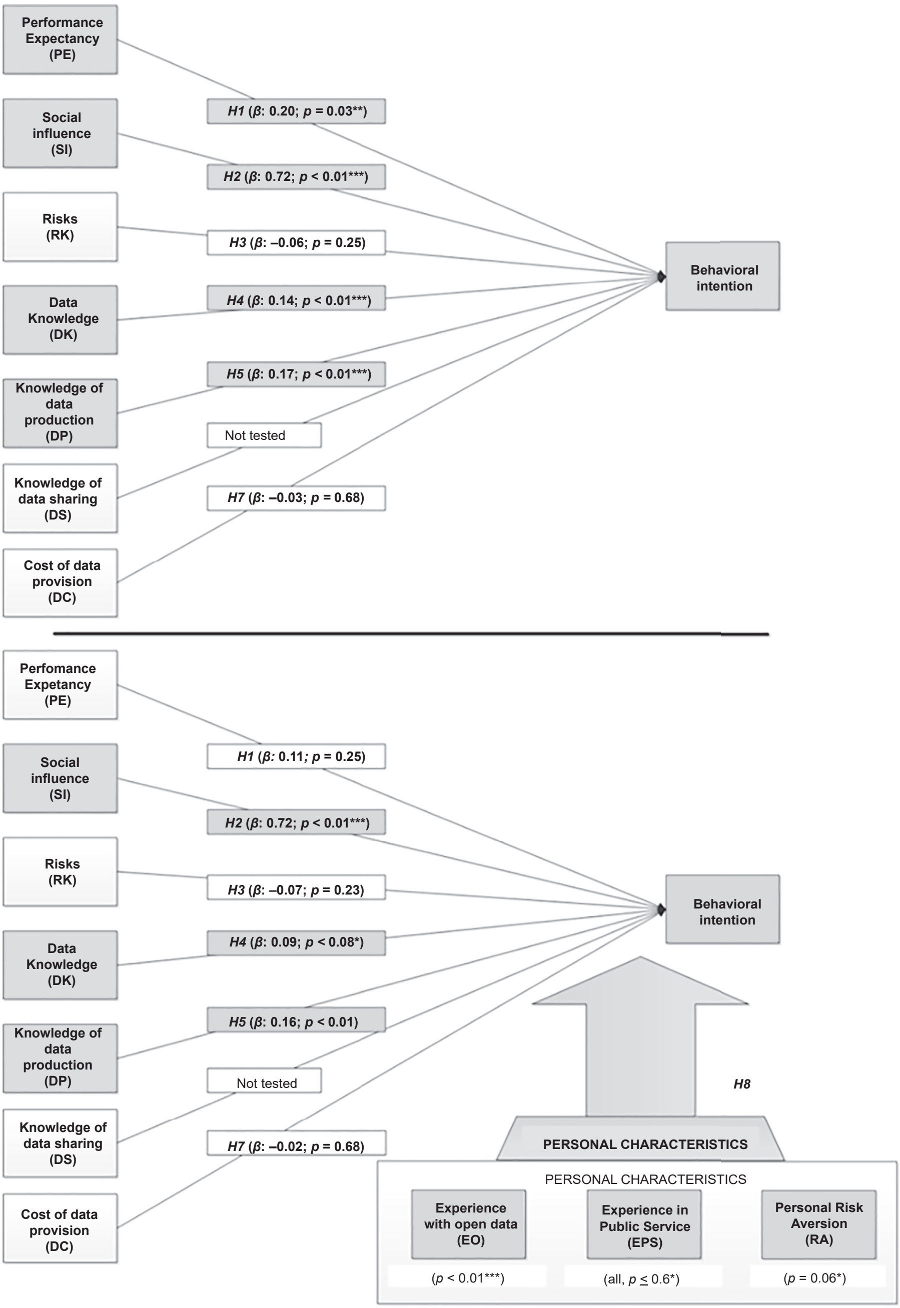

Figure 2.
Model differences

inclusion of personal characteristics. Here, a ceiling effect appears as many of the respondents declared high levels of previous knowledge to open data. To our knowledge, no other study tested DK or knowledge of data opening, even though it was mentioned as relevant in the literature (Denis and Goeta, 2017; Hossain *et al.*, 2016; Janssen *et al.*, 2012). A better knowledge of data management and open data creates a higher willingness to open data. This finding reinforces that education and training can improve BI for supporting open data.

The results show that the relationship between PE and BI is influenced by personal characteristics, which reduced its coefficient by half, as it lowered the level of statistical significance to a nonstatistically significant level. These results indicate that previous experience with open data and the duration to which civil servants work in governments (personal characteristics) might change the way benefits are perceived. We included *usefulness* as part of our PE construct. In contrast to the findings of Wirtz and Piehler (2016), who found usefulness to be the most important independent variable, and Weerakkody *et al.* (2017), who found the perceived usefulness of open data as their strongest predictor, PE was not statistically significant in terms of influencing BI. As these authors did not test personal characteristics in their model, this moderating effect could explain the difference.

The item DC ("The costs of providing public sector data are too high") resulted in a very low statistical significance in the final regression ($t = -0.418$, $p = 0.68$). In our case, the perception of these costs was not found to be as influential to BI, as previous studies indicated (Bozeman and Kingsley, 1998; Denis and Goeta, 2017).

Moreover, RK ($t = -1.267$, $p = 0.23$) was hardly influenced by personal characteristics and had a low statistical significance. Whereas Hardy and Maurushat (2017) and Hossain *et al.* (2016) found knowledge of benefits or better assessment of RK to be influential, these constructs' effects were not found to influence civil servants' BI to open more data significantly. Our findings confirmed previous research findings that perceived bureaucratic decision barriers and perceived hierarchical barriers have a significant impact on BI towards open government data (Ruijer and Meijer, 2019; Wirtz *et al.*, 2016). *SI* was also found to be highly significant in our sample.

Lastly, our research has different outcomes than Wirtz *et al.* (2016), who found that "perceived risk-related attitude of the administrative employees has the most potent relationship to the open government data resistance" (p.1352), RK were the least significant for our case. The authors' sample was composed of an older audience; however, they did not capture the respondents' governmental work experience. The differences in time that civil servants have been working for governments could be one explanation for the divergence from our findings.

5.2 The influence of personal characteristics

Insights were also obtained from the *personal characteristics* of the participating civil servants in the model. The time to which these professionals have worked for governments, their previous experience with open data, and their personal aversion for risk were found to be significantly affecting the model. These effects indicate that actions to promote the opening of data might be adjusted for specific audiences. Gender, level of government (local or national), and the type of contract that civil servants have with the government were found to have no influence.

Related to the time to which a civil servant has been working for the government, the shorter their experience is, the greater the intention to open data. Specifically, civil servants working less than 10 years in government ($t = 2.70$, $p < 0.01$) were found to be willing to open data. This suggests that civil servants might become more risk-averse over the years (Lipsky, 1971). Furthermore, more experienced civil servants might be more difficult to influence. Also, previous experience with open data ($t = 2.66$, $p < 0.01$) show considerable strength in changing the influence of model factors for predicting the BI of civil servants. This change suggests that the more civil servants have known or used open data, the more they tend to support it.

As the environment of bureaucracy tends to be more rigid than the private sector (West and Raso, 2012), adding clarity to rules, commands and support for releasing data might have a strong significant effect. Hence, if governments want to increase civil servants' support to open data, they should focus on making legal framework and giving clear commands through hierarchical means.

5.3 Limitations

The present study has several limitations. First, the data is collected on the Brazilian context local and the Federal government. Brazil has more than 190 million inhabitants having cultural differences between segments and regions. Though Brazil's open data policy national policies outstanding position in the last decade, the analysis lacks comparability to other countries and backgrounds The diversity of cultures in Brazil might result in better generalization; however, other countries and cultures might yield different outcomes. Additionally, more accurate behavioral insights can come from exploring the differences within the category of civil servants, differentiating the diverse set of professionals who are likely to have distinct relationships with open data.

We identified factors from the literature by taking a deductive approach. Other factors might be relevant and, in the future, an inductive qualitative approach based on observation and in-depth case studies could be used to identify more factors and to understand the complexity.

Another limitation originates from our sample. Significant effects on variables, such as RK or PE might be confirmed when the sample would be bigger. Also, the fact that years of experience in governments makes a significant difference for BI suggests that the characteristics of the civil servants do matter. As such, generalization to populations having dissimilar characteristics should be done with care. In particular, the generalization to the general public, as their personal characteristics is likely to deviate from civil servants.

6. Conclusion

Whereas there is research about the adoption of open data by users, civil servants' behavioral intention to open data is hardly researched in the literature, whereas civil servants make decisions to open data. The findings show that Social Influences, Data management knowledge, and risks have a significant influence on the behavioral intention of civil servants to support open data. These effects are controlled by personal characteristics. In contrast to literature about open data users, Social Influence was found to be the most important factor for civil servants. Hence, this factor needs to be addressed to reduce resistance and increase support to open data. Our construct includes the legislation and legal frameworks that civil servants deal with on a daily basis.

Social Influence assesses the possibilities already in place for civil servants to make the data public. The hierarchy and institutional decision-making processes are also part of the main efforts to let civil servants open more data. Making hierarchy and decision-making processes explicit for civil servants is likely to increase their support for sharing data. Additionally, the more knowledge civil servants have of data management policies, the higher their behavioral intentions to support data opening. Also, the behavior intention increased once civil servants start realizing that data is produced in almost every administrative activity.

The target audience was found to be relevant to improve interventions as some personal characteristics of civil servants also have an influence. Particularly, previous experience with open data content and personal aversion to risk was influential for the individual attitudes towards open data. Age, gender, type of contract with public administration or the government level that civil servants are working (national or local) did not show any statistical relevance. These factors need to be taken into account when generalizing the outcomes.

6.1 Research and practical implications

Our work adds to the limited knowledge of factors influencing the support of civil servants to open data. We create the first model for explaining factors of influence on civil servants' behavioral intention at the individual level. The present study extends the open data research to the data provider side in the first paper aiming at the factors for civil servant's attitude change towards open data. This is also the first paper to hypothesize each of the factors in a model, and test them using data collected from 387 civil servants using quantitative methods. Our adoption model for civil servants' behavioral intentions to support open data increases knowledge of the influencing factors and shows that demographics and personal characteristics can influence adoption.

Policymakers and activists intending to increase civil servants' support for open data provision are advised to focus their actions on making rules and the hierarchy for the opening of data clear. Additionally, making more intelligible data opening processes and informing better the results should also increase support for opening data by civil servants.

Although Brazil has a variety of cultures, further research is recommended to test our findings in greater samples with a more diverse background, including different countries. Particularly, it is important to confirm our findings that perceptions of risks or benefits involved in data opening were not significantly influential to civil servants' intentions to support the opening of data. The literature on technology adoption suggests otherwise and might make open data provision a special case in the field of open government.

Nevertheless, the presented model is a step towards a better understanding of civil servants' behavior intention to open data, which can be used as the basis for improving policies to increase governmental data release.

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(The Appendix follows overleaf)

Appendix

Constructs' measurement items

The questionnaire presented the following questions to be answered on a scale of 1–7 (7 = completely agree, and 1 = completely disagree).

Behavioral intention Code Behavioral intention		Content	Reference
BI_11	BI_21	I already provide open public sector data in my work	(Wirtz *et al.*, 2016; Zuiderwijk *et al.*, 2015)
BI_12	BI_22	I intend to provide open public sector data in the future	(Venkatesh *et al.*, 2003; Zuiderwijk *et al.*, 2015)
BI_13	BI_23	I predict that I will provide open public sector data in the future	(Venkatesh *et al.*, 2003; Zuiderwijk *et al.*, 2015)

Performance expectancy Code Social influence		Content The environment to make public sector data accessible to the public	Reference
SI_11	SI_21	People who are important to me think that I should provide open public sector data	(Venkatesh *et al.*, 2003; Weerakkody *et al.*, 2017)
SI_12	SI_22	License and legal frameworks make it difficult to provide public sector data	Janssen *et al.* (2012)
SI_13	SI_23	Providing public sector data is not a priority for me	Moore and Benbasat (1991)
SI_14	SI_24	Providing public sector data is not a priority for the office I work for	Venkatesh and Davis (2000)
SI_15	SI_25	I have the necessary autonomy to provide public sector data	(Wirtz *et al.*, 2016; Zuiderwijk *et al.*, 2015)
SI_16	SI_26	My work does not require me to provide open public sector data	Zuiderwijk *et al.* (2015)
SI_17	SI_27	My superiors expect me to provide open public sector data	(Venkatesh and Davis, 2000; Zuiderwijk *et al.*, 2015)
SI_18	SI_28	I have assistance available concerning the provision of open public sector data	Venkatesh *et al.* (2003)

DK Code Lack of knowledge		Content Public sector data in my actual work	Reference
LK_13	LK_23	I know how to make the public sector data available for others to access	Venkatesh *et al.* (2003)
EE_11	EE_21	I clearly understand how to provide open public sector data	(Venkatesh *et al.*, 2003; Zuiderwijk *et al.*, 2015)
EE_16	EE_26	Learning to provide open public sector data will be easy for me	(Venkatesh *et al.*, 2003; Zuiderwijk *et al.*, 2015)

Risks Code		Content	Reference
RK_11	RK_21	The public sector data that results from my work cannot be shared for privacy issues	Hossain *et al.* (2016)
RK_12	LK_22	The public sector data that results from my work cannot be shared for security issues	Hardy and Maurushat (2017)

Table A1.
Constructs' measurement items with references

(*continued*)

Risks Code		Content	Reference
RK_13	RK_23	Providing public sector data is a threat	Venkatesh *et al.* (2003)
RK_14	RK_24	I fear individual privacy by providing public sector data	(Moore and Benbasat, 1991; Venkatesh *et al.*, 2003)
RK_15	RK_25	I fear people will have false conclusions if public sector data is provided	Weerakkody *et al.* (2017)

Additional features Code Lack of knowledge		Content Public sector data in my actual work	Reference
DP_11	DP_21	I produce public sector data in my work	(Venkatesh and Davis, 2000; Zuiderwijk *et al.*, 2015)
DS_11	DS_21	Some public sector data can be shared	(Venkatesh and Davis, 2000; Weerakkody *et al.*, 2017)
DC_11	DC_21	The costs of providing public sector data are too high	Conradie and Choenni (2014)

Personal characteristics Experience in the public sector Code	Content Public sector data in my actual work	Categories
EPS_11	How long have you been working in the public sector?	0–5 years, 5+ to 10 years, 10+ to 15 years, 15+ to 20 years, 20+ years
EPS_12	Since you have started working for the public sector, which of the following better describes your most common role	Operational, Technical, Advisory, Decision-maker, other
EPS_13	Which was your last work relation with the public sector	Appointed, Elected, Permanent Staff, Hired, other

Experience with open public sector data Code	Content Public sector data in my actual work
EO_11	I have heard about public sector data before
EO_12	I have studied public sector data before
EO_13	I have used public sector data before

Personal risk aversion Code	Content Public sector data in my actual work
RA_11	I feel comfortable to share my data on the Internet
RA_12	I would go against the law to reach an important goal
RA_13	I feel positively excited with the unexpected
RA_14	Professional stability is the most important thing in my life

Demographics Code	Content	Categories
Age	Which year were you born?	
Gender		Female, Male, other
Group	Which level of government do you work for?	Local, Federal, other

Table A1.

About the authors

Fernando Kleiman is a lecturer in the Engineering Systems and Services Department of the Technology, Policy and Management Faculty at Delft University of Technology. His current research interests lie in digital government, open data and serious gaming. Fernando Kleiman is the corresponding author and can be contacted at: fekleiman@gmail.com

Dr Sylvia J.T. Jansen works as assistant professor in the department of Management in the Built Environment of the Faculty of Architecture and the Built Environment at Delft University of Technology. Her teaching activities include courses on research skills and statistics. Her research focuses on cognitive aspects and well-being, such as preferences, satisfaction, quality of life, attitude and values.

Professor dr.ir. Sebastiaan Meijer is full Professor in health care logistics and department head of Biomedical Engineering and Health Systems at KTH Royal Institute of Technology, Stockholm, Sweden. He works particularly on large-scale system change with support of gaming and simulation methods, with applications in health and transport. For more information, see: www.kth.se/mth

Professor Dr Marijn Janssen is a full Professor in Information and Communication Technology (ICT) and Governance at the Technology, Policy and Management Faculty of Delft University of Technology, The Netherlands. He was ranked as one of the leading e-government researchers and has published over 500 refereed publications. For more information, see: www.tbm.tudelft.nl/marijnj