Citizens' Trust in Open Government Data

A Quantitative Study about the Effects of Data Quality, System Quality and Service Quality

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ABSTRACT

Previous research assumes that poor quality of Open Government Data (OGD), OGD portals, and the services provided for OGD may result in reduced trust of citizens in OGD. However, studies that empirically test this assumption are scarce. Using the Information Systems (IS) Success Model as a theoretical basis, this study aims to examine the effects of data quality, system quality, and service quality on citizens' trust in OGD. We used Structural Equation Modeling (SEM) to analyze the 200 responses to our online questionnaire. We found that trust in OGD can be predicted by citizens' perceptions of OGD system quality and service quality. Furthermore, citizens' perception of service quality positively influences their perceptions of data and system quality, whereas citizens' perception of system quality positively influences their perception of data quality. This study is among the first that quantitatively examines the effects of data quality, service quality, and system quality on citizen's trust in OGD. It contributes to the scientific literature by providing an operationalization of elements of the IS Success Model in the context of OGD and by developing and applying a model of factors influencing citizen's trust in OGD. While previous research finds that perceived data quality is the most crucial driver for trust in OGD, our study finds that citizens' perception of OGD service quality is a more important driver for trust in OGD. With regard to the practical contributions of this study, open data policymakers should be aware that citizens' perceptions on data quality can be greatly improved when appropriate human services are provided (e.g., designated civil servants offering support or help to data users) in addition to the provision of OGD portal functionalities (e.g., data visualization and comparison tools).

CCS CONCEPTS

• **Information systems**; • **Social and professional topics** → Computing / technology policy;

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KEYWORDS

Open Government Data, data quality, systems quality, service quality, trust, Information Systems Success Model, citizen engagement, Structural Equation Modeling

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1 INTRODUCTION

In the past two decades, public bodies have increasingly shared their raw datasets online with the public [4, 19, 44]. One important motivation for this development is the belief that opening up government data will increase citizens' trust in government [10]. Previous research found that the level of citizen's trust in government has been declining for more than three decades now [40]. Therefore, governments look for ways to become more transparent and increase citizens' trust. The underlying assumption is that if citizens can trust OGD, their trust in government will also increase.

Previous research already provides some insights into the factors associated with the utilization of OGD and citizen's trust. For example, Meijer et al. [26] studied OGD use and its influence on trust in the context of open data provision of two governmental agencies in the Netherlands. They found that when the results of data reuse can be replicated, trust is improved. As another example, Jurisch et al. [21] surveyed international citizens from six different countries to examine the effect of the citizens' trust in the Internet on their intention to use OGD. They found that trust does not influence the intention to use OGD.

The relationship between OGD use and citizen's trust has also been studied from various theoretical perspectives. For example, Zuiderwijk [49] used the integrated Unified Theory of Acceptance and Use of Technology and the two-stage expectation confirmation theory of Information Systems continuance by Venkatesh et al. [41] to investigate the effects of an OGD infrastructure on the coordination of OGD use. She found that the use of an OGD infrastructure, including an OGD portal and the quality of the data, sometimes leads to trust-related concerns. As another example, Weerakkody et al. [46] used an adjusted model based on Rogers' diffusion of innovations theory [33] to empirically investigate the predictors

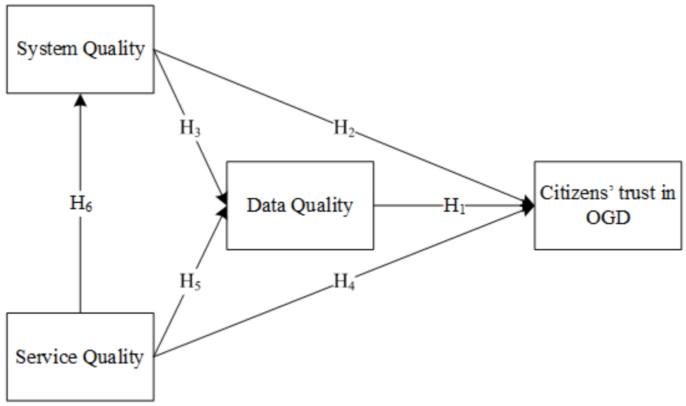

Figure 1: Research model for investigating the effects of data quality, system quality, and service quality on trust in OGD.

influencing the use of public sector open data. Their findings implicitly suggest that most citizens have no concerns about trusting OGD.

Existing studies that address both OGD use in relation to trust-aspects have two main constraints. First, current studies that examine OGD effects on trust mainly focus on the system that provides access to open data (e.g., open data platforms [6], open data websites [44]), or OGD in general [38, 47]. On the other hand, the IS Success Model of DeLone and McLean [12] hypothesizes that not only the quality of the system but also the quality of the data and the provided service quality affect trust levels. Despite a few exceptions (e.g., [38]), most studies do not integrate these different quality aspects. Second, a large proportion of the studies concerning OGD use in relation to trust investigates the influence of citizens' trust on the use of OGD, rather than the other way around. Research into the relationship between OGD utilization as the independent variable and the trust of citizens as the dependent variable is scarce. The relationship between OGD use and trust is usually assumed rather than tested empirically, and more empirical research is needed to verify this assumption [35].

Using the IS Success Model of DeLone and McLean [12] as a theoretical basis, this study aims to examine the effects of data quality, system quality, and service quality on citizens' trust in OGD. To attain this objective, we created and administered an online survey, and empirically analyzed 200 responses collected from the survey distribution throughout open data user communities. This paper is among the first to scientifically contribute to applying the IS Success Model in the context of OGD use. Our study also provides insight into the quality attributes of OGD that should be taken into account by policymakers who are responsible for OGD provision to enhance citizens' trust.

This paper is structured as follows. First, we discuss the theoretical background to introduce the variables relevant to our research model and hypotheses development. Next, we present our research design, which includes data collection and analysis, and describes the results in the following section. Then, we discuss our empirical study results. Finally, we present our conclusion, which also highlights the limitations of our study and provides a possible avenue for future research.

2 RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

The hypotheses underlying the IS Success Model are often amended to suit better the context of the study (e.g., [6, 38]). We adjusted the original IS Success Model to suit better the context of OGD, based on relevant literature concerning citizens' trust in OGD. Figure 1 shows the modified model for investigating the effects of data quality, system quality, and service quality on trust in OGD. The developed hypotheses and the modifications are explained in the following subsections.

2.1 Trust

Trust can be defined as "the confidence a person has in his or her favorable expectations of what other people will do, based, in many cases, on previous interactions" [13, p. 726]. The creation of the trust is one of the expected benefits of opening government data [19, p. 261]. Trust can be produced based on three different modes: 1) *process-based trust*, related to past or expected exchange, 2) *characteristic-based trust*, linked to person based on social characteristics, and 3) *institutional-based trust*, referred to formal societal structures based on individual or firm-specific attributes [48]. Process-based trust is probably the most relevant in the context of OGD use; citizens' prior experience with governmental organizations and the opened data that they provide shape trust. While trust in e-government service is composed of trust in government and trust in the Internet [5], we argue that, in line with Zuiderwijk [49], trust in OGD is a combination of *trust in government* and *trust in the opened data.*

2.2 Data Quality

In the IS Success Model, information quality measures the information system output, namely, the quality of the information produced by the system, mainly in the form of reports [11]. Data quality is typically related to technical attributes of data, while information quality concerns non-technical issues [24]. In this study, we do not distinguish between data quality and information quality. We prefer to use the term data quality over information quality to represent both technical and non-technical attributes of data. Data quality can be defined as "data that are fit for use by data consumers" [43,

p. 6]. Thus, it is subjective since its attributes are positively related to data users' preferences [42]. For example, a group of users would require timely and relevant data for making a prompt decision, while others need accurate data to create a report.

Low quality of data has been a recurring barrier found in many open data studies (e.g., [2, 25, 28, 50]) that can result in less trust in the opened data and the data provider, i.e., the government [19, 27, 49]. Contrary, improved information quality of e-government services in the United Kingdom has a positive and significant effect on citizens' trust [45]. Lee and Levy [23] suggest that accuracy, completeness, and representation are three specific attributes of information quality that influence trust. Similarly, open data scholars find that inaccurate, incomplete, and unknown formatted data, as well as data that is difficult to link with other data, have become recurring impediments of open data use [50]. The improvement of these quality attributes of open data, namely *accuracy*, *completeness*, *format*, and *interoperability*, can result in higher citizens' trust in OGD. Thus, we hypothesize:

H1: Perceived open government data quality will positively influence citizens' trust in open government data.

2.3 System Quality

System quality is defined as the measures of the system's information processing performance from a combination of the engineering-oriented evaluation and user-oriented perspectives [11]. Weerakkody, Irani, Lee, Hindi and Osman [45] found that the improved system quality of e-government services in the United Kingdom had a positive and significant effect on citizens' trust. Systems or technologies or platforms that provide access to open data and their functionalities that enable users to explore and exploit data are critical ingredients to OGD programs [6]. Such a system usually manifests in an open data website or portal. Citizens can use these portals to search for datasets, visualize, and download them [50] or even develop applications on top of it [19]. Charalabidis, Loukis and Alexopoulos [6] evaluate a European OGD infrastructure and find that the portal's response time can be a significant problem to data users. Also, the way citizens can use OGD is significantly contingent upon the way these portals publish the open data [4]. The availability of guidance or documentation in the portal can reduce the complexity when using open data, which, in turn, will improve trust in OGD [19]. Building on these arguments, the improvement of the following four attributes of system quality, namely, *availability*, *functionality*, *responsiveness*, and *documentation*, can lead to higher citizens' trust in OGD. Thus, we formulate the following hypothesis:

H2: Perceived open government data system quality will positively influence citizens' trust in open government data.

The early version of the OGD portal typically functions merely as a website for locating open data and viewing the datasets. At the same time, the advanced version also provides a set of online tools or technologies for exploring and exploiting data [1]. These technologies help users better understand and manipulate open data to create something out of it. For example, documentation such as metadata describes the structure of data, and a guide explains the way users can utilize the datasets would substantially improve users' perceptions of data quality. Functionalities provided on the data portal that enables data visualization, comparison, and linking would also enhance citizens' perceptions of data quality. Therefore, we hypothesize that a relationship exists between the perceived system quality and data quality in which higher system quality will lead to higher data quality. Thus, we hypothesize:

H3: Citizens' perceived open government data system quality will positively influence the perceived open government data quality.

2.4 Service Quality

Service quality is rooted in marketing studies and can be defined as a comparison of consumer service expectations with perceived service performance [29]. Since the mid-1980s, IS organizations typically provide not only information as the output of the systems they developed, but also support or help for the end-users of the IS and its outputs [12]. Tan et al. [39] reveal that the high quality of e-government service improves citizens' trust towards public e-service. Services can take form as an IT-mediated tool such as guides for open data users [19] or features for rating the quality of data and submitting comments on it [50]. Services in the form of designated civil servants providing support or help to data users are typically offered in open data hackathons [31] and rarely given in the daily operation of OGD provision; the case of Stockholm Public Transport is an exception to this in which support for feedback is provided [34].

The underlying dimensions of the service quality attributes are 1) *tangibles* (physical appearance of personnel), 2) *reliability* (ability to perform the promised service), 3) *responsiveness* (willingness to help and provide prompt service), 4) *assurance* (knowledge and courtesy of employees and their ability to inspire trust and confidence), and 5) *empathy* (caring, individualized attention the service provider gives its customers) [20, 30]. The non-existence of support, help, or training for the use of the data and interaction and discussions between OGD users and providers are typical barriers found in open data use [37, 50]. The availability of services for data users having a higher quality of reliability, assurance, responsiveness, and empathy can result in higher trust in OGD. Therefore, we hypothesize:

H4: Perceived open government data service quality will positively influence citizens' trust in open government data.

Bharati and Berg [3] find that information quality and system quality, among other factors, indirectly influence the service quality of a company IS department through employee IS performance. Higher quality of system used by employees and information it produces lead to higher employee performance, which then increases the quality of services provided by the employees. We argue that the opposite directions are applied in the OGD context. Reliable, assuring, responsive, and empathic OGD services will result in higher perceived data quality as well as higher perceived system quality. For example, responsive and emphatic personnel who receive feedback from users and make follow-ups such as correcting inaccurate data may enhance the users' perceptions of data quality. Also, knowledgeable and responsive civil servants designated to data support may ease the efforts needed by users to operate data exploitation-related functionalities provided in the portal and hence, improve the users' perceptions of OGD system quality. Therefore, we formulate the following hypotheses:

H5: Citizens' perceived open government data service quality will positively influence the perceived open government data quality.

H6: Citizens' perceived open government data service quality will positively influence the perceived open government system quality.

3 RESEARCH DESIGN

3.1 Instrument Development

An online questionnaire was developed to collect data about citizens' perceptions of data quality, system quality, and service quality, as well as their trust in OGD. The questionnaire consisted of three sections: 1) questions concerning the participant's experience in engaging with OGD (those who declare that they never use OGD had to exit the questionnaire), 2) questions seeking to obtain the participant's perceptions of data quality, system quality, service quality, and the participants' trust in OGD, and 3) questions about the participant's background. The questions in the second section were primarily adopted from and have been tested by DeLone and McLean [11], DeLone and McLean [12], Gefen [13], Parasuraman, Zeithaml and Berry [29], and Carter and Bélanger [5]. Also, the questions were slightly reworded to fit the context of the study. Table 1 presents the question items asked in the second part of the questionnaire. A five-point Likert scale was used to specify the level of citizens' agreement or disagreement on the perceptions asked, ranging from "strongly disagree" to "strongly agree." Furthermore, a "not applicable" option was provided. These questions have been made available online through the 4TU Research Data repository at http://doi.org/10.4121/uuid:28fea23d-6984-4ed5-9755-3064988331f0.

3.2 Data Collection

The survey link was distributed from May to September 2019 through various open data community channels such as mailing lists and LinkedIn groups. We recruited survey participants using this opportunistic sampling approach because defining the boundaries of potential OGD citizen-user communities is challenging. More notably, the opening of government data leads to use by unpredicted actors [2]. We collected 471 responses, over which 203 have missing values because some questions are left unanswered. Among the remaining responses (n=268), eight have "not applicable" answers for the dependent variables (questions related to trust), and sixty have "not applicable" answers for the independent variables (questions related to data quality, system quality, and service quality). According to Hair et al. [16], these responses can be removed from the sample. Therefore, we excluded these 271 responses and included 200 complete responses (42.46%) in the analysis.

3.3 Data Analysis

Structural Equation Modeling (SEM) is a technique able to simultaneously examine multiple relationships between dependent and independent variables [15]. SEM enables researchers not only to evaluate the hypothesized causation among a set of dependent and independent constructs (*structural model*) but also to assess the loadings of observed items (*indicators*) on their expected latent variables (*measurement model*) [14, 16]. Our research aims to examine the effects of OGD quality constructs – data, system, and service quality – on trust in OGD, implying that both structural and measurement model has to be assessed, and therefore, SEM is selected. In this study, we employ Partial Least Squares (PLS)-SEM as an approach for our data analysis using the computer program "SmartPLS 3" [32].

4 RESULTS

We followed the two-stage assessment of PLS-SEM results as proposed by Hair et al. [17]: 1) the evaluation of the measurement model for examining the relationships between constructs and their latent variables (indicators), and 2) the assessment of the structural model for considering the causation among constructs. In the first stage, the measurement models are assessed on their internal consistency reliability, convergent validity, and discriminant validity to provide evidence of the measures' quality. After the constructs' reliability and validity have been examined, the structural model estimates are reviewed in the second stage based on the coefficients of determination (R^2 values), the significance of the path coefficients, f^2 effect sizes, and predictive relevance (Q^2).

4.1 Respondents Characteristics

From the available responses, we can infer that slightly more than two-thirds of the respondents were men, and more than three-quarters of the respondents were between 22 and 50 years old. Almost three-quarters of the respondents engaged with OGD already more than five years ago, suggesting that most respondents have relatively much experience with OGD use. More than half of all respondents use OGD in a team setting (n=117, 58.5%). The three most popular types of output created by the respondents through OGD use include visualizations (20.4%), applications (19.2%), and maps (17.2%). Table 2 describes the characteristics of our questionnaire respondents. The last column of the table shows the percentage of the valid sample that is calculated only based on completed answers; the calculation excludes missing values.

More than half of the respondents have Indonesian nationality (n=94; 60.3%), and this may raise a question whether their perspectives biased the response of the whole sample. Before doing the PLS-SEM analysis, we assessed the sample using the Kruskal-Wallis H test to determine whether there are significantly differences between groups of nationality on all variables asked in the survey. The results show that there were no statistically significant differences in the perceptions of data quality, system quality, service quality, and trust between the different citizen's nationality groups. Therefore, we can confidently proceed with the analysis.

4.2 Measurement Model Assessment

Reflective measurement models are assessed on their internal consistency reliability, convergent validity, and discriminant validity to provide evidence of the measures' quality [17]. Overall, our constructs appear to be satisfactorily reliable, having composite reliability (CR) and Cronbach's $\alpha > 0.8$ [7]. The indicators' loadings > 0.708 and reliability > 0.5, and our constructs' AVE > 0.6 imply that the constructs have high levels of convergent validity [17]. Our constructs' confidence interval of the heterotrait-monotrait ratio (HTMT) statistic does not include the value 1 and thus indicates that the constructs are empirically distinct [17]. Based on these results, we can conclude that the construct measures are reliable

Table 1: Measurement items.

Construct	Question items (indicators)	
Data Quality (DQ)	DQ1	The open government data I engaged with are free from errors
	DQ2	The open government data I engaged with are complete (i.e., cover all attributes needed, no missing value)
	DQ3	The open government data I engaged with are well-formatted
	DQ4	It is easy to link or combine a dataset to/with other open government data
Systems Quality (SYSQ)	SYSQ1	The open government data portal that I engaged with is available at all times
	SYSQ2	The open government data systems that I engaged with responds at an acceptable speed
	SYSQ3	The open government data systems that I engaged with provides functionalities needed (e.g., data visualization, feedback mechanism, quality rating)
	SYSQ4	The open government data systems that I engaged with provided guidance and documentation to download and interpret the data
Service Quality (SVCQ)	SVCQ1	The open government data provider responds sufficiently timely
	SVCQ2	The open government data provider follows up on a user's report
	SVCQ3	The open government data provider has adequate knowledge to answer a user's request
	SVCQ4	The open government data provider prioritizes the user's needs
Trust (TR)	TR1	Open government data providers can be trusted
	TR2	The open government data that I engaged with seemed truthful to me
	TR3	The open government data I engaged with can be trusted

Table 2: Characteristics of respondents and their experience in using OGD (n=200).

Characteristic	Category	Sample		
		N	%	Valid %
Gender	Female	50	25.0	32.9
	Male	102	51.0	67.1
	Unknown (missing)	48	24.0	
Age	22-30 years old	23	11.5	13.9
	31-40 years old	63	31.5	40.4
	41-50 years old	45	22.5	28.8
	51-60 years old	19	9.5	12.2
	61 years old or over	6	3.0	3.8
	Unknown (missing)	44	22.0	
Have engaged with OGD since	≥ 5 years ago	146	73.0	
	2 years ≥ and < 5 years ago	24	12.0	
	1 year ≥ and < 2 years ago	20	10.0	
	Less than 1 year	10	5.0	
Nationality	African	2	1.0	1.3
	American	8	4.0	5.1
	Asian – Indonesian	94	47.0	60.3
	Asian – non Indonesian	4	2.0	2.6
	Australian	4	2.0	2.6
	European	43	21.5	27.6
	Other	1	0.5	0.6
	Unknown (missing)	44	22.0	

and valid (see Table 3 for a complete overview), and thus, the next assessment on the structural model can be conducted.

4.3 Structural Model Assessment

The structural model assessment involves examining the predictive capabilities of the model and the relationships between the constructs [17]. This examination was carried out in a systematic approach comprised of six assessment procedures: 1) collinearity issues, 2) significance and relevance, 3) level of R^2, 4) f^2 effect size, and 5) predictive relevance Q^2. Before analyzing all assessment results, collinearity problems found in the first step (i.e., when variance inflation factor or VIF value is above 5), must be solved by

Table 3: The assessment results of the measurement model.

Constructs	Items	Convergent Validity			Internal Consistency Reliability		Discriminant Validity
		Loadings	Indicator Reliability	AVE	Composite Reliability	Cronbach's α	HTMT
DQ	DQ1	0.833	0.694	0.737	0.918	0.881	Yes
	DQ2	0.884	0.781				
	DQ3	0.876	0.767				
	DQ4	0.839	0.704				
SYSQ	SYSQ1	0.765	0.585	0.647	0.880	0.818	Yes
	SYSQ2	0.810	0.656				
	SYSQ3	0.841	0.707				
	SYSQ4	0.799	0.638				
SVCQ	SVCQ1	0.886	0.785	0.805	0.943	0.919	Yes
	SVCQ2	0.907	0.823				
	SVCQ3	0.899	0.808				
	SVCQ4	0.897	0.805				
TR	TR1	0.916	0.839	0.864	0.950	0.921	Yes
	TR2	0.932	0.869				
	TR3	0.940	0.884				

removing indicators having problematic VIF values [17]. The VIF values of all sets of predictors in our model are clearly below the threshold of 5. Table 4 presents the result of the structural model assessment.

Following the rule of thumb described by Chin [8] – R^2 values of 0.67, 0.33, or 0.19 for endogenous latent variables are respectively substantial, moderate, or weak –, the R^2 values of *DQ* (0.420) and *SYSQ* (0.548) can be considered moderate. In contrast, the R^2 value of *TR* (0.326) is weak. The values of f^2 can be assessed using the guidelines proposed by Cohen [9]; values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects of the exogenous latent variable. Following the guidelines, we can infer that *DQ* has no impact on *TR*, while *SYSQ* has a small effect size on *TR* and *DQ* as well as *SVCQ* on *TR* and *DQ*. On the contrary, *SVCQ* has a large effect size on *SYSQ*.

Looking at the relative importance of the exogenous driver constructs for trust in OGD (*TR*), one can find that citizens' perception of OGD service quality (*SVCQ*) is most important, followed by the perception of system quality (*SYSQ*) and data quality (*DQ*) respectively. The results also show clearly that the citizens' perception of service quality (*SVCQ*) is the most important driver for the perception of data quality (*DQ*), followed by the perception of system quality (*SYSQ*).

Concerning the trust in OGD, we can see that among the three exogenous driver constructs, the citizens' perception of service quality has the strongest total effect on trust (0.527), followed by citizens' perception of system quality (0.283) and citizens' perception of data quality (0.145). Assuming a typical 5% significance level [17], we find that all relationships in the structural model, except DQ → TR, are significant. Figure 2 depicts the path coefficients of relationships among variables in the research model. The Q^2 values of all three endogenous constructs are considerably above zero – TR (0.268), DQ (0.298), and SYSQ (0.347) – and therefore, the results provide clear support for the model's predictive relevance regarding the endogenous latent variables.

5 DISCUSSION

Since our research aims to investigate the OGD users' perceptions of data, system, and service quality and examine whether these perceptions affect their trust in OGD, we sampled only those who have experience in using OGD. Interestingly, almost three-quarters of the respondents have engaged with OGD for more than five years. This finding suggests that despite recurring barriers of OGD use found in many case studies throughout the last decade (e.g., [2, 10, 25, 50]), some citizens are interested in OGD and want to do something with it (e.g., creating apps for society [36], participating in open data hackathons [18]). Since trust is shaped by the experience of trustors (the citizens) when interacting with trustees (the governments as data providers and the data that they opened) [48], perceptions of these experienced respondents are crucial.

Based on the loading and reliability assessments, *DQ2*, *SYSQ3*, and *SVCQ2* appear to be the most important attributes of the perceived data quality, system quality, and service quality, respectively. *DQ2* concerns the completeness of the opened data, *SYSQ3* is associated with the functionalities provided in the OGD portal, while *SVCQ2* is related to the responsiveness of OGD provider to users' reports. In previous research, partial or incomplete data, among other barriers, is found to discourage the use of OGD among social science researchers [19, 50] and among the top three data quality barriers [2]. Functionalities of OGD portal that support users' data processing capabilities such as data enrichment, data cleansing, linking datasets, data visualization (e.g., data preview, mapping), and multiple data layering have the most substantial impact on the OGD value creation [6] and influence the OGD usability [28]. In line with the findings of previous research, lack of support or helpdesk is found to impede OGD use [28, 50] and the provision of

Table 4: The assessment results of the structural model.

	f^2	Path Coefficients	Total Effects	t Values	p Values	Hypothesis supported/ rejected
H_1: DQ → TR	0.018	0.145	0.145	1.890	0.063	rejected
H_2: SYSQ → TR	0.036	0.239	0.283	2.608*	0.010	supported
H_3: SYSQ → DQ	0.069	0.298	0.298	3.240*	0.001	supported
H_4: SVCQ → TR	0.041	0.260	0.527	3.227*	0.001	supported
H_5: SVCQ → DQ	0.122	0.396	0.616	4.081**	0.000	supported
H_6: SVCQ → SYSQ	1.213	0.740	0.740	20.568**	0.000	supported

Notes: two-tailed tests, significant at: *p<0.01, t-value 2.57; **p<0.001, t-value 3.29.

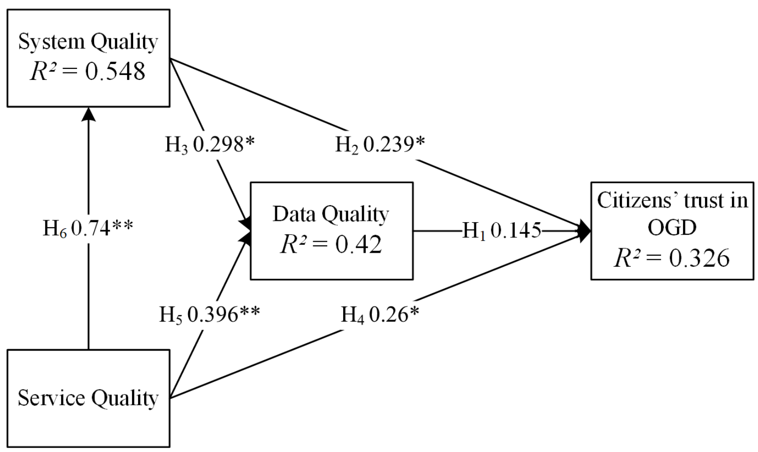

Figure 2: Path coefficients for relationships among data quality, system quality, service quality, and trust in OGD. Notes: two-tailed tests, significant at: *p<0.01, t-value 2.57; **p<0.001, t-value 3.29.

support can lower users' task complexity [36], our result further shows that responsiveness is the most crucial attribute of OGD support.

While previous research finds that perceived data quality is the most important driver for trust in OGD (e.g., [19, 27, 49]), our study finds that citizens' perception of OGD service quality is a more important driver for trust in OGD. The difference in findings may be related to the level of experience of the citizens involved in the study. Some previous studies might view trust from the lens of *new* or *first-time users* who may have a lack or even no experience in using OGD that varies in quality. In contrast, in line with several other studies (e.g., [22]), our respondents were relatively *experienced users* who might have skills needed to curate and cleanse raw OGD. Once the experienced users found *low*-quality data, they might want to discuss it with the data provider, provide feedback, and demand follow-up actions to correct the data [50]. In this sense, exemplified by a case study in Sweden [34], the quality of support provided by the OGD provider would be far more critical than the quality of the opened data as the latter can be reconciled during a feedback mechanism.

Our assessment results also show that citizens' perception of OGD service quality is a more critical driver of perceived data quality compared to the perception of OGD system quality. We argue that although OGD portals provide functionalities needed by the users to analyze and manipulate raw data, there exist technological limitations that prevent the implementation of more advanced features such as statistical analysis [1]. Users have to rely on their own or their colleagues' knowledge and skills, such as analytical techniques for collecting, analyzing, interpreting and presenting data [19]. This could be compensated by support or help provided by knowledgeable, responsive, and emphatic data providers.

Although OGD provision has been widely studied in the last decade, research on the use of OGD is still at infancy. More notably, no empirical research examining the effects of perceived OGD quality on citizens' trust in OGD has been done. According to Hair, Hult, Ringle and Sarstedt [17, p. 196], when a study is exploratory in nature, on many occasions, researchers assume a significance level of 10%. Using this assumption, hypothesis H_1 can be supported. However, we assume the typical significance level of 5% and therefore, reject the hypothesis H_1, indicating that the perceptions of data quality do not affect citizens' trust. This striking finding strongly implies that experienced users prefer OGD availability over its quality because they or their groups possess sufficient knowledge and skills to overcome data quality problems.

6 CONCLUSION

Using the Information Systems (IS) Success Model as a theoretical basis, this study aims to examine the effects of data quality, system quality, and service quality on citizens' trust in OGD. We distributed a comprehensive questionnaire and collected the responses of 200 citizens from 27 nationalities. More than three-quarters of the respondents have more than two years of experience in engaging with OGD.

We used the PLS-SEM approach to analyze the 200 questionnaire responses, and we found that trust in OGD can be predicted by citizens' perception of OGD system quality and service quality. All hypotheses, except the influence of citizens' perception of data quality on trust, are supported. Furthermore, citizens' perception of service quality positively influences citizens' perception of data and system quality, whereas the perception of system quality positively influences citizens' perception of data quality. While previous research finds that perceived data quality is the most important driver for trust in OGD, our study finds that citizens' perception of OGD service quality is a more important driver for trust in OGD.

This study provides useful insights for practitioners and open data policymakers. Our findings show that open data policymakers should be aware that citizens' perceptions on data quality can be significantly improved when appropriate human services are provided (e.g., designated civil servants offering support or help to data users) in addition to the provision of OGD portal functionalities (e.g., data visualization and comparison tools). The availability of knowledgeable, responsive, and empathic support or help from an OGD provider will not only be invaluable for the experienced users who can curate and cleanse low-quality data but also for the first-time users to compensate for their lack of data curation and cleaning skills. For experienced users, the feedback mechanism as an aspect of OGD service can encourage the correction and improvement of low-quality data.

Our study contributes to the scientific literature by providing an operationalization of elements of the Information Systems Success Model in the context of OGD and by developing a model of factors influencing citizen's trust in OGD. This study is among the first that quantitatively examines the effects of data quality, service quality, and system quality on citizen's trust in OGD. Few studies that use the theories separately are limitedly available, but to the best of our knowledge, research that integrates the application of the two theories in the OGD context is non-existent.

This study focused on citizens' perceived data quality, system quality, and service quality, yet we did not investigate particular OGD that the respondents had used, nor the systems and services. Since OGD provision highly varies across different governmental organizations, thus it cannot be separated from its context, which includes the nature of the opened data, the nature of the portal providing access to data, and services offered to data users. Therefore, our research can be complemented by looking into these particular aspects using, for example, a multiple case study approach. Furthermore, our study models citizens' perceptions of OGD quality, human systems that are both geographically and temporally dynamic. We recommend future research to longitudinally investigate the effects of OGD quality attributes on citizens' trust in OGD and examine additional factors that may influence citizens' trust in OGD to better understand how the antecedents of trust in OGD change over time.

REFERENCES

[1] ALEXOPOULOS, C., ZUIDERWIJK, A., CHARAPABIDIS, Y., LOUKIS, E., and JANSSEN, M., 2014. Designing a Second Generation of Open Data Platforms: Integrating Open Data and Social Media. In International Conference on Electronic Government 2014, Guimarães, Portugal, 230-241.

[2] BENO, M., FIGL, K., UMBRICH, J., and POLLERES, A., 2017. Open Data Hopes and Fears: Determining the Barriers of Open Data. In Proceedings of the 2017 Conference for E-Democracy and Open Government (CeDEM) (Krems, Austria, 17-19 May 2017).

[3] BHARATI, P. and BERG, D., 2003. Managing Information Technology for Service Quality: A Study from the Other Side. INFORMATION TECHNOLOGY & PEOPLE 16, 2, 183-202. DOI= http://dx.doi.org/10.1108/09593840310478685.

[4] BRAUNSCHWEIG, K., EBERIUS, J., THIELE, M., and LEHNER, W., 2012. The State of Open Data: Limits of Current Open Data Platforms In Proceedings of the 21th International World Wide Web Conference (Lyon, French2012).

[5] CARTER, L. and BÉLANGER, F., 2005. The utilization of e-government services: citizen trust, innovation and acceptance factors. Information Systems Journal 15, 1, 5-25. DOI= http://dx.doi.org/10.1111/j.1365-2575.2005.00183.x.

[6] CHARALABIDIS, Y., LOUKIS, E., and ALEXOPOULOS, C., 2014. Evaluating Second Generation Open Government Data Infrastructures Using Value Models. In Proceedings of the 47th Hawaii International Conference on System Sciences (Hicss) (2014), 2114-2126. DOI= http://dx.doi.org/10.1109/Hicss.2014.267.

[7] CHEN, J.V., JUBILADO, R.J.M., CAPISTRANO, E.P.S., and YEN, D.C., 2015. Factors affecting online tax filing - An application of the IS Success Model and trust theory. Computers in Human Behavior 43, 251-262. DOI= http://dx.doi.org/10.1016/j.chb.2014.11.017.

[8] CHIN, W.W., 1998. The partial least squares approach to structural equation modeling. In Modern Methods for Business Research, G.A. MARCOULIDES Ed. Lawrence Erlbaum Associates, Mahwah, NJ, 295–358.

[9] COHEN, J., 1992. A power primer. Psychological Bulletin 112, 1, 155–159. DOI= http://dx.doi.org/10.1037/0033-2909.112.1.155.

[10] CRANEFIELD, J., ROBERTSON, O., and OLIVER, G., 2014. Value in the MASH: Exploring the Benefits, Barriers and Enablers of Open Data Apps. In Proceedings of the 22nd European Conference on Information Systems (ECIS 2014) (Tel Aviv, Israel, 9-11 June 2014).

[11] DELONE, W.H. and MCLEAN, E.R., 1992. Information Systems Success: The Quest for the Dependent Variable. Journal of management information systems 3, 1, 60-95.

[12] DELONE, W.H. and MCLEAN, E.R., 2003. The DeLone and McLean model of information systems success: a ten-year update. Journal of management information systems 19, 4, 9-30. DOI= http://dx.doi.org/10.1080/07421222.2003.11045748.

[13] GEFEN, D., 2000. E-commerce: the role of familiarity and trust. Omega 28, 6, 725-737. DOI= http://dx.doi.org/10.1016/S0305-0483(00)00021-9.

[14] GEFEN, D., STRAUB, D., and BOUDREAU, M.-C., 2000. Structural Equation Modeling and Regression: Guidelines for Research Practice. Communications of the Association for Information Systems 4, 7.

[15] GERBING, D.W. and ANDERSON, J.C., 1988. An Updated Paradigm for Scale Development Incorporating Unidimensionality and Its Assessment. Journal of Marketing Research 25, 2, 186-192. DOI= http://dx.doi.org/10.1177/002224378802500207.

[16] HAIR, J.F., BLACK, W.C., BABIN, B.J., and ANDERSON, R.E., 2014. Multivariate Data Analysis: A Global Perspective. Pearson Education Limited, Essex, England.

[17] HAIR, J.F., HULT, G.T.M., RINGLE, C.M., and SARSTEDT, M., 2017. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). SAGE Publications, Inc., Los Angeles.

[18] HIVON, J. and TITAH, R., 2017. Conceptualizing citizen participation in open data use at the city level. Transforming Government: People, Process and Policy 11, 1, 99-118. DOI= http://dx.doi.org/10.1108/TG-12-2015-0053.

[19] JANSSEN, M., CHARALABIDIS, Y., and ZUIDERWIJK, A., 2012. Benefits, Adoption Barriers and Myths of Open Data and Open Government. Information Systems Management 29, 4, 258-268. DOI= http://dx.doi.org/10.1080/10580530.2012.716740.

[20] JIANG, J.J., KLEIN, G., and CARR, C.L., 2002. Measuring Information System Service Quality: SERVQUAL from the Other Side. MIS quarterly 26, 2, 145-166. DOI= http://dx.doi.org/10.2307/4132324.

[21] JURISCH, M.C., KAUTZ, M., WOLF, P., and KRCMAR, H., 2015. An International Survey of the Factors Influencing the Intention to use Open Government. In Proceedings of the 48th Hawaii International Conference on System Sciences (HICSS) (Kauai, Hawaii2015), 2188-2198. DOI= http://dx.doi.org/10.1109/Hicss.2015.262.

[22] KUK, G. and DAVIES, T., 2011. The Roles of Agency and Artifacts in Assembling Open Data Complementarities. In Proceedings of the International Conference on Information Systems 2011 (Shanghai, China, 04-07 Dec 2011).

[23] LEE, A. and LEVY, Y., 2014. The effect of information quality on trust in e-government systems' transformation. Transforming Government: People, Process and Policy 8, 1, 76-100. DOI= http://dx.doi.org/10.1108/TG-10-2012-0011.

[24] MADNICK, S.E., WANG, R.Y., LEE, Y.W., and ZHU, H., 2009. Overview and Framework for Data and Information Quality Research. Journal of Data and Information Quality 1, 1, 2-22. DOI= http://dx.doi.org/10.1145/1515693.1516680.

[25] MARTIN, C., 2014. Barriers to the Open Government Data Agenda Taking a Multi-Level Perspective. Policy & Internet 6, 3, 217-240.

[26] MEIJER, R., CONRADIE, P., and CHOENNI, S., 2014. Reconciling contradictions of open data regarding transparency, privacy, security and trust. Journal of Theoretical and Applied Electronic Commerce Research 9, 3, 32-44. DOI= http://dx.doi.org/10.4067/S0718-18762014000300004.

[27] O'HARA, K., 2012. Data Quality, Government Data and the Open Data Infosphere. In Proceedings of the AISB/IACAP World Congress 2012: Information Quality Symposium (Birmingham, UK, 3 Jul 2012), 223-232.

[28] OJO, A., PORWOL, L., WAQAR, M., STASIEWICZ, A., OSAGIE, E., HOGAN, M., HARNEY, O., and ZELETI, F.A., 2016. Realizing the Innovation Potentials from Open Data: Stakeholders' Perspectives on the Desired Affordances of Open Data Environment. In Proceedings of the PRO-VE 2016: Collaboration in a Hyperconnected World (Porto, Portugal, 3-5 October 2016).

[29] PARASURAMAN, A., ZEITHAML, V.A., and BERRY, L.L., 1985. A Conceptual Model of Service Quality and Its Implications for Future Research. Journal of Marketing 49, 4, 41-50.

[30] PITT, L.F., WATSON, R.T., and KAVAN, C.B., 1995. Service Quality: A Measure of Information Systems Effectiveness. MIS quarterly 19, 2, 173-187. DOI= http://dx.doi.org/10.2307/249687.

[31] PURWANTO, A., ZUIDERWIJK, A., and JANSSEN, M., 2018. Group Development Stages in Open Government Data Engagement Initiatives: A Comparative Case Studies Analysis. In EGOV 2018, P. PARYCEK, O. GLASSEY, M. JANSSEN, H.J. SCHOLL, E. TAMBOURIS, E. KALAMPOKIS and S. VIRKAR Eds. Springer, Krems, Austria. DOI= http://dx.doi.org/10.1007/978-3-319-98690-6_5.

[32] RINGLE, C., WENDE, S., and BECKER, J.-M., 2015. SmartPLS 3 SmartPLS GmbH, Boenningstedt.

[33] ROGERS, E.M., 1962. Diffusion of innovations. Free Press, New York.

[34] RUDMARK, D., ARNESTRAND, E., and AVITAL, M., 2012. Crowdpushing: The flip Side of Crowdsourcing. In Proceedings of the 20th European Conference on Information Systems (ECIS'12) (Barcelona, Spain, 11-13 Jun 2012).

[35] SAFAROV, I., MEIJER, A., and GRIMMELIKHUIJSEN, S., 2017. Utilization of open government data: A systematic literature review of types, conditions, effects and users. Information Polity 22, 1, 1-24. DOI= http://dx.doi.org/10.3233/IP-160012.

[36] SMITH, G., OFE, H.A., and SANDBERG, J., 2016. Digital Service Innovation from Open Data: Exploring the Value Proposition of an Open Data Marketplace. 2016 49th Hawaii International Conference on System Sciences (Hicss), 1277-1286. DOI= http://dx.doi.org/10.1109/Hicss.2016.162.

[37] SUSHA, I., GRÖNLUND, Å., and JANSSEN, M., 2015. Organizational measures to stimulate user engagement with open data. Transforming Government: People, Process and Policy 9, 2, 181-206. DOI= http://dx.doi.org/10.1108/TG-05-2014-0016.

[38] TALUKDER, M.S., SHEN, L., TALUKDER, M.F.H., and BAO, Y., 2019. Determinants of user acceptance and use of open government data (OGD): An empirical investigation in Bangladesh. Technology in Society 56, 147-156. DOI= http://dx.doi.org/10.1016/j.techsoc.2018.09.013.

[39] TAN, C.-W., BENBASAT, I., and CENFETELLI, R.T., 2008. Building citizen trust towards e-government services: Do high quality websites matter? In Proceedings of the Annual Hawaii International Conference on System Sciences. DOI= http://dx.doi.org/10.1109/HICSS.2008.80.

[40] TOLBERT, C.J. and MOSSBERGER, K., 2006. The Effects of E-Government on Trust and Confidence in Government. Public Administration Review 66, 3, 354-369. DOI= http://dx.doi.org/10.1111/j.1540-6210.2006.00594.x.

[41] VENKATESH, V., THONG, J.Y.L., CHAN, F.K.Y., HU, P.J.-H., and BROWN, S.A., 2011. Extending the two-stage information systems continuance model: incorporating UTAUT predictors and the role of context. Information Systems Journal 21, 6, 527–555. DOI= http://dx.doi.org/10.1111/j.1365-2575.2011.00373.x.

[42] WANG, D., RICHARDS, D., and CHEN, C., 2018. An Analysis of Interaction Between Users and Open Government Data Portals in Data Acquisition Process. In 15th Pacific Rim Knowledge Acquisition Workshop, PKAW 2018, K. YOSHIDA and M. LEE Eds. Springer, Nanjing, China, 184-200.

[43] WANG, R.Y. and STRONG, D.M., 1996. Beyond Accuracy: What Data Quality Means to Data Consumers. Journal of management information systems 12, 4, 5-33. DOI= http://dx.doi.org/10.1080/07421222.1996.11518099.

[44] WEERAKKODY, V., IRANI, Z., KAPOOR, K., SIVARAJAH, U., and DWIVEDI, Y.K., 2017. Open data and its usability: an empirical view from the Citizen's perspective. Information Systems Frontiers 19, 2, 285–300. DOI= http://dx.doi.org/10.1007/s10796-016-9679-1.

[45] WEERAKKODY, V., IRANI, Z., LEE, H., HINDI, N., and OSMAN, I., 2016. Are U.K. Citizens Satisfied With E-Government Services? Identifying and Testing Antecedents of Satisfaction. Information Systems Management 33, 4, 331-343. DOI= http://dx.doi.org/10.1080/10580530.2016.1220216.

[46] WEERAKKODY, V., KAPOOR, K., BALTA, M.E., IRANI, Z., and DWIVEDI, Y.K., 2017. Factors influencing user acceptance of public sector big open data. Production Planning & Control 28, 11-12, 891–905. DOI= http://dx.doi.org/10.1080/09537287.2017.1336802.

[47] WIRTZ, B.W., WEYERER, J.C., and RÖSCH, M., 2018. Citizen and Open Government: An Empirical Analysis of Antecedents of Open Government Data. International Journal of Public Administration 41, 4, 308-320. DOI= http://dx.doi.org/10.1080/01900692.2016.1263659.

[48] ZUCKER, L.G., 1986. Production of trust: Institutional sources of economic structure, 1840–1920. Research in Organizational Behavior 8, 53–111.

[49] ZUIDERWIJK, A., 2015. Open data infrastructures: The design of an infrastructure to enhance the coordination of open data use TU Delft, Delft. DOI= http://dx.doi.org/10.4233/uuid:9b9e60bc-1edd-449a-84c6-7485d9bde012

[50] ZUIDERWIJK, A., JANSSEN, M., CHOENNI, S., MEIJER, R., and ALIBAKS, R.S., 2012. Socio-technical impediments of open data. Electronic Journal of eGovernment 10, 2, 156-172.