EVALUATING THE IMPACT OF OPEN DATA USING PARTIAL LEAST SQUARES STRUCTURAL EQUATION MODELING

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Abstract: *Governments around the world are opening up their data to the public. This paper develops the issue of open data and their impact. More precisely, it evaluates how can be open data as a resource transformed to generate the impact and added value for the public sector. The main aim is to propose a new model, which uses attributes of open data in the context of the e-government development. The model consists of five enabling factors and five generating mechanisms (collaboration, efficiency, participation, transparency and innovation). To show the causal relationships between these constructs, the method of partial least squares structural equation modeling was chosen. By understanding the relationships, governments can improve their actions and investments in the context of e-government and related open data initiatives. The results suggest that the focus should be on the support of collaboration, participation and innovation processes in the public sector.*

Keywords: *Open data, Public sector, E-government, Initiatives, Partial least squares, Structural equation modeling.*

JEL Classification: *C39, C52, H83, L86, O38.*

Introduction

Open government is a recent phenomenon in which public sector data are made available and can be used by everybody for what it seems an unlimited amount of purposes [3]. Opening data may allow citizens and businesses to analyze various datasets and understand what governments are spending public resources on. Hence, many governments have started creating interoperability and open data frameworks spanning boundaries between public sector institutions, citizens and businesses to manage their data in a transparent and efficient way [9], [14]. The emergence of open data use is another phase of the Information and Communication Technologies (ICT) revolution and the public sector is at the center of the current shift to openness [10].

Although, the debate about open data is often reduced to open government data (OGD), there are also other type of open data such as open business data (OBD), open citizen data (OCD) and open science data (OSD). OGD are the most interesting subset of open data because such subsets have already been collected for specific use, have been paid for by taxpayers, are relevant and offer value beyond what is captured from the originally intended use. When opened up, government data become a common, shared resource (i.e., public good) that is provided by the government [7]. In 2012 and again in 2014, the United Nations issued OGD for their E-Government Survey reports, which summarized how governments utilized these data to better serve and protect their people [14]. However, OGD have limited impact if these data are not evaluated in the context of enabling factors and focus on developing sustainable ecosystems of users, which involve their collaboration, participation, innovation, etc.

1 Literature review

1.1 Open data and open government initiatives

The literature on reuse of open data often circles around their potentials [3] and the economic value of government data, while the literature on open government is in a higher grade directed towards government policy and centered on how use of open data can contribute to the generation of social value in collaborative settings [7]. As mentioned above, interest in the concept of open data has been around for many years [6]. Various studies have confirmed that releasing public data in open formats creates considerable benefits for citizens, businesses, researchers, and other stakeholders to understand public or private problems in new ways through advanced data analytics [2], [3], [6], [10], [13].

Open data are a piece of content or data if anyone is free to use, reuse, and also redistribute it – subject only, at most, to the requirement to attribute and share-alike. Most of open data are actually in raw form. However, republishing does imply citing the original source not only to give credit but to ensure that the data has not been modified or results misrepresented [6], [10]. Kucera and Chlapek [10] presented a set of benefits that can be achieved by publishing OGD and a set of risks that should be assessed when a dataset is considered for opening up. Cowan, Alencar and Mcgarry [2] used practical examples in an attempt to illustrate many of the related issues and allied opportunities of open data.

Open government acts as an umbrella term for many different ideas and concepts. The definition of open government mostly consists of transparency, participation and collaboration of the state towards third actors like the economy or the citizenship. Most often, open government is equated with e-government and the usage of ICT [3], [13]. The number of open data initiatives has grown from two to over three hundred in the period 2009–2013 [7], and the membership in the Open Government Partnership (OGP) has gone from eight in 2011 to the sixty-five participating countries in 2015. Governments are initiating open data initiatives as a new approach where external stakeholders can play an increased role in the innovation of government services. This is unlike previous approaches of e-government service innovation where services are solely initiated and developed by the agencies themselves [2], [8], [14], [17]. By promoting openness of government data, governments hope to enhance transparency, public efficiency, participation, collaboration and innovation of government services through the reorganizing, re-packaging, and synthesizing information from various sources [3], [17]. These open government principles are then best viewed as initiatives that government takes to accomplish defined objectives that provide the opportunity to achieve greater or additional value through incorporating these democratic practices [8], [10]. Social media can also play an important role in inspiring or enabling OGD usage, and in involving communities of practice, formed by people who engage in a process of collective learning related to OGD to sustain relevant initiatives and help create a network of actors [13].

Kalampokis, Tambouris and Tarabanis [8] claim that the real value of OGD will unveil from performing data analytics on top of combined statistical datasets that were previously closed in disparate sources and can now be linked to provide unexpected and unexplored insights. To support this claim, authors described the OGD analytics concept along with its technical requirements, which can be later extended with Apache Hadoop. Contributing to this trend is the increasing government recognition of the economic potential of open data [17]. Kalampokis, Tambouris and Tarabanis [9] also revised existing e-government stage models and proposed an OGD stage model, which provides a roadmap for OGD reuse and enables evaluation of relevant initiatives' sophistication. Vickery [15] suggests that the economic value from the exploitation of OGD surpasses government investments in collecting, interpreting and disseminating the data. Jetzek, Avital and Bjørn-Andersen [7] developed a conceptual model portraying how open data as a resource can be transformed to value. Geiger and von Lucke [3] then analyzed the added value of freely-accessible government data and discussed challenges of OGD for public sector at the different administration levels. A cost-benefit analysis often shows the impact and value of taking the time to facilitate access [13]. Solar, Concha and Meijueiro [12] proposed an open data maturity model to assess the commitment and capabilities of public agencies in pursuing the principles and practices of open data, which has a hierarchical structure consists of domains, sub-domains and critical variables.

1.2 Structural equation modeling and partial least squares regression

Structural equation modeling (SEM) is the first generation path modeling widely used by researchers and practitioners to analyze the interrelationship among variables in a model. Some of the researchers classify SEM as the covariance-based SEM (CB-SEM). However, this method has been argued since its application should achieve the criterion before conducting the measurement and structural model. Thus, partial least squares SEM (PLS-SEM) was established to solve this problem [1], [5]. Afthanorhan [1] then compared CB-SEM and PLS-SEM, examined which one of these structural equation modeling methods is appropriate to use for confirmatory factor analysis and concluded that PLS-SEM is more reliable and valid.

Its application is aimed to maximize the explained variance of the endogenous latent variables (dependent) by estimating partial model relationships in an iterative sequence of ordinary least squares (OLS) regressions, and minimize the unexplained variances [1], [5]. Latent variables are underlying variables that cannot be observed directly, they are also known as constructs or factors [16]. The most frequently cited reasons to use PLS-SEM are related to small sample sizes, non-normal data, the use of formatively measured latent variables, and also the unrestricted use of single attribute constructs. Other substantive reasons for choosing PLS-SEM can be found in [4] or [11], where authors provided comprehensive guidelines to aid researchers in avoiding common pitfalls in the PLS-SEM use. PLS-SEM is not appropriate for all kinds of statistical analysis. There are also some weaknesses such as [16]: since arrows are always single headed, it cannot model undirected correlation; high-valued structural path coefficients are needed if the sample size is small; it may create large mean square errors in the estimation of path coefficient loading, etc.

There are two sub-models in a structural equation model, the inner model specifies the relationships between the independent and dependent latent variables, whereas the outer model specifies the relationships between the latent variables and their observed indicators, which can be measured directly, they act as indicators for an underlying latent variable [5], [16]. In the SEM, a variable is either exogenous or endogenous. An exogenous variable has path arrows pointing outwards and none leading to it. Meanwhile, an endogenous variable has at least one path leading to it and represents the effects of other variables [16].

Outer model assessment involves examining individual indicator (attribute) reliabilities, the reliabilities for each construct's composite of measures (i.e., internal consistency reliability), and also the measures' convergent and discriminant validities. When evaluating how well constructs are measured by their indicators, individually or jointly, researchers need to distinguish between reflective and formative measurement perspectives [4]. While criteria such as Cronbach's alpha and composite reliability are commonly applied to evaluate reflective measures, an internal consistency perspective is inappropriate for assessing formative ones. Also formative measures' convergent and discriminant validities cannot be assessed by empirical means [4], [5], [11].

2 Problem formulation and research methodology

OGD change the role of the public sector to the information publisher, which in turn may result in a change of power distribution between the public and private sectors as well as between the government and the public, where are chances that the work of the government will improve due to increased collaboration, participation, innovation, efficiency, transparency, which will subsequently strengthen democracy.

The aim of this paper is to evaluate how can be open data as a resource transformed to generate the impact and added value for the public sector. The proposed model uses five enabling factors and five generating mechanisms to evaluate the impact. To show the causal relationships between these constructs, the PLS-SEM is chosen. Authors' model is then based on the conceptual model of OGD value generation, which was developed by Jetzek, Avital and Bjørn-Andersen [7]. However, their model used data from 2011-2012 including some attributes, which do not exist anymore in 2015. Also frameworks of some the indices used were reworked, especially the Web Index by World Wide Web Foundation (W3F). Furthermore, new trends such social media or open data portals arise and have to be incorporated into the new model. Finally, they evaluated only 61 countries. The new model evaluates 86 countries, which offers a bigger sample size. It also solves the problem of the validation of constructs by using only the attributes supported by the literature review.

The PLS-SEM method was chosen, as this study is exploratory due to the emergent state of the phenomenon, use of formative constructs, the small sample size and the complexity of the structural model [4], [5]. Since PLS is based on a series of OLS regressions, it has minimum demands regarding sample size, and generally achieves high levels of statistical power [5]. The main tool used is SmartPLS 3, because it is freely available to the research community. Furthermore, this software has maintained an active online discussion forum, providing a good platform for knowledge exchange among its users. Data pre-processing and basic operations on them are conducted in Microsoft Excel 2010.

3 Research study

3.1 Model description and data sources

The main changes in the new model, which is shown in the Table 1, are as follows: In the first construct, three attributes had to be removed, because they don't exist anymore in 2015. Extent of open government initiative was moved to the data governance construct. These new attributes were thus added to the data openness and freedom construct: personal data protection laws/regulations, legal requirements for Net neutrality, safeguards to protect privacy of electronic communications, right to information/freedom of information law and freedom of the press. Three attributes had to be also removed from the data governance construct, three others were added: government success in ICT promotion, effective legal protection from cybercrime and use of web-powered ICTs to catalyze action. Also two attributes of the capabilities and readiness construct don't exist in 2015. They were replaced by the Human Capital Index, quality of the educational system and use of web-powered ICTs to improve education outcomes. Infrastructure and connectivity construct still consist of firm level technology absorption and Telecommunication Infrastructure Index, however, the structure of this index changed (three new attributes were added into this index). International Internet bandwidth (bit/s) per Internet user, Secure Internet servers per one million people and availability of latest technologies were added. Accessibility of digital content was then moved to the new construct – relevant content and use, together with Online Service Index, which was moved from the data governance construct. This new construct also consist of blocking/filtering of web content.

Attributes of the efficiency construct remained the same. The only two attributes of the innovation construct don't exist anymore. Therefore, four new attributes were added: Global Innovation Index, capacity for innovation, government procurement of advanced technology products and The Patent Cooperation Treaty patent applications. One attribute from the transparency construct had to be removed and was replaced by the Corruption Perceptions Index. The e-participation index is still the main part of the participation construct, although, the structure of the index used was changed in 2014 [14]. The second attribute of this construct is voice and accountability, which reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. The new collaboration construct then consists of use of virtual social networks and cooperation in labor-employer relations.

The focus of the last construct was changed from "value" to "impact", when three attributes remained, one was replaced by the social performance and the data source of the environmental impact was changed from the Natural Resource Management Index to the Environmental Performance Index because of outdated data (only data from 2011 are available).

Tab. 1: Description of the exogenous type of constructs, attributes and data source 1/2

Construct	Attribute	Type (measure)	Data source
Capabilities and Readiness (CR)	1.1 Human Capital Index	Exogenous (reflective)	UN
	1.2 Quality of the educational system		WEF
	1.3 Extent of staff training		WEF
	1.4 Use of web-powered ICTs to improve education outcomes		W3F
Data Governance (DG)	2.1 Importance of ICTs to government vision of the future	Exogenous (formative)	WEF
	2.2 Government success in ICT promotion		WEF
	2.3 Extent of open government initiative		W3F
	2.4 Effective legal protection from cybercrime		W3F
	2.5 Use of web-powered ICTs to catalyze action		W3F
Data Openness and Freedom (DOF)	3.1 Personal data protection laws/regulations	Exogenous (formative)	W3F
	3.2 Legal requirements for Net neutrality		W3F
	3.3 Safeguards to protect privacy of electronic communications		W3F
	3.4 Right to information/freedom of information		W3F
	3.5 Freedom of the press		Freedom House

Source: Authors

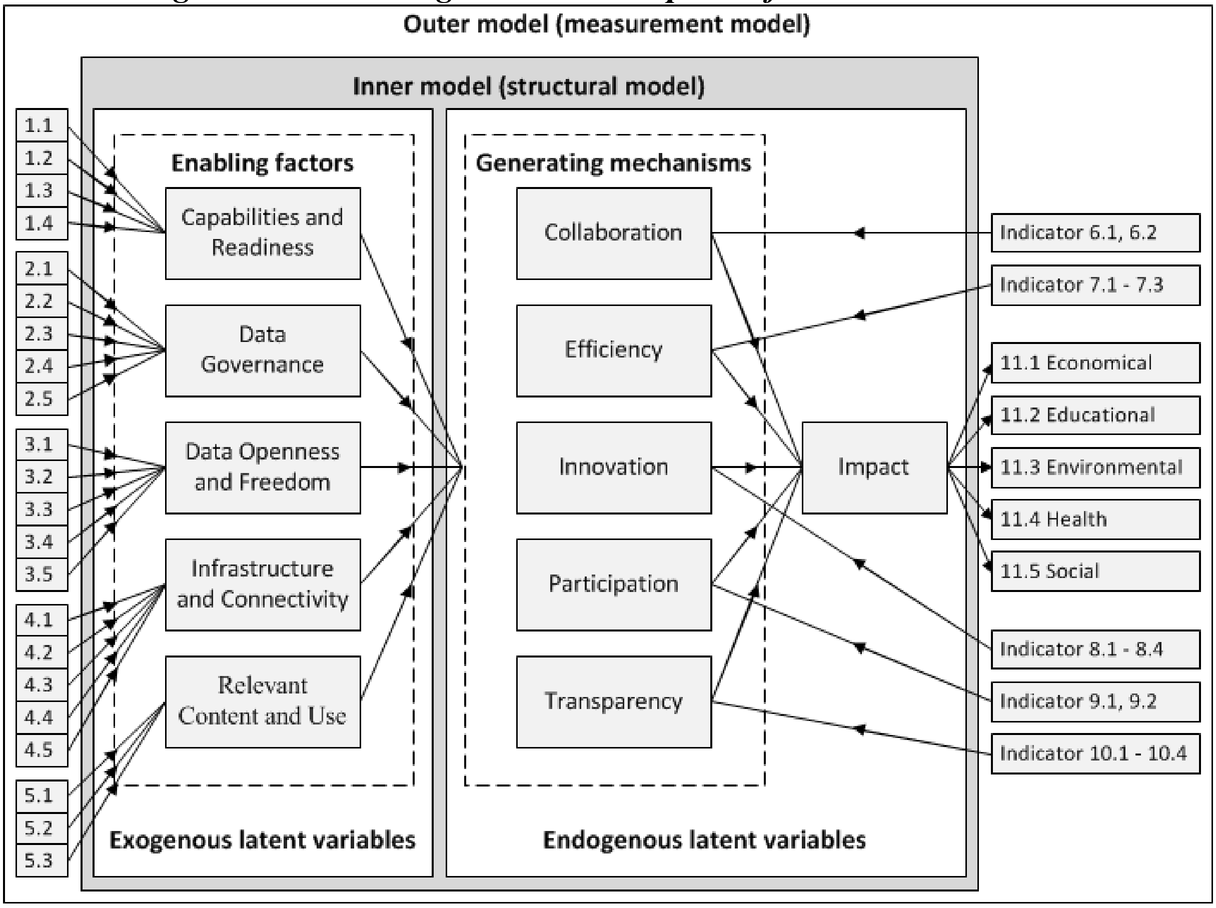
Tab. 1: Description of the endogenous type of constructs, attributes and data source 2/2

Infrastructure and Connectivity (IC)	4.1 Telecommunication Infrastructure Index	Exogenous (reflective)	UN
	4.2 International Internet bandwidth (bit/s) per Internet user		ITU
	4.3 Availability of latest technologies		WEF
	4.4 Secure Internet servers per one million people		World Bank
	4.5 Firm level technology absorption		WEF
Relevant Content and Use (RCU)	5.1 Online Service Index	Exogenous (formative)	UN
	5.2 Accessibility of digital content		WEF
	5.3 Blocking/filtering of web content		W3F
Collaboration (COL)	6.1 Use of virtual social networks	Endogenous (reflective)	WEF
	6.2 Cooperation in labor-employer relations		WEF
Efficiency (EFF)	7.1 ICT use and government efficiency	Endogenous (reflective)	WEF
	7.2 Government effectiveness		World Bank
	7.3 Ease of doing business index		World Bank
Innovation (INN)	8.1 Global Innovation Index	Endogenous (reflective)	INSEAD
	8.2 Capacity for innovation		WEF
	8.3 Government procurement of advanced technology products		WEF
	8.4 The Patent Cooperation Treaty patent applications (all types)		WEF
Participation (PAR)	9.1 e-Participation Index	Endogenous (reflective)	UN
	9.2 Voice and accountability		World Bank
Transparency (TRA)	10.1 Corruption Perceptions Index	Endogenous (reflective)	Transparenc y International
	10.2 Transparency of government policymaking		WEF
	10.3 Judicial independence		WEF
	10.4 Irregular payments and bribes		WEF
Impact (IMP)	11.1 Economical: GDP/capita	Endogenous (reflective)	World Bank
	11.2 Educational: Education index		UN
	11.3 Environmental: Environmental Performance Index		Yale and Columbia University
	11.4 Health: Health index		UN
	11.5 Social: Human Development Index		UN

Source: Authors

In this research study, constructs are made from a maximum of five indicators, and the impact has the largest structural equation with five direct paths pointing towards it. Inner and outer model in a SEM diagram can be seen from the Fig. 1.

Fig. 1: The SEM diagram and description of the related elements



Source: Authors

3.2 Data analysis

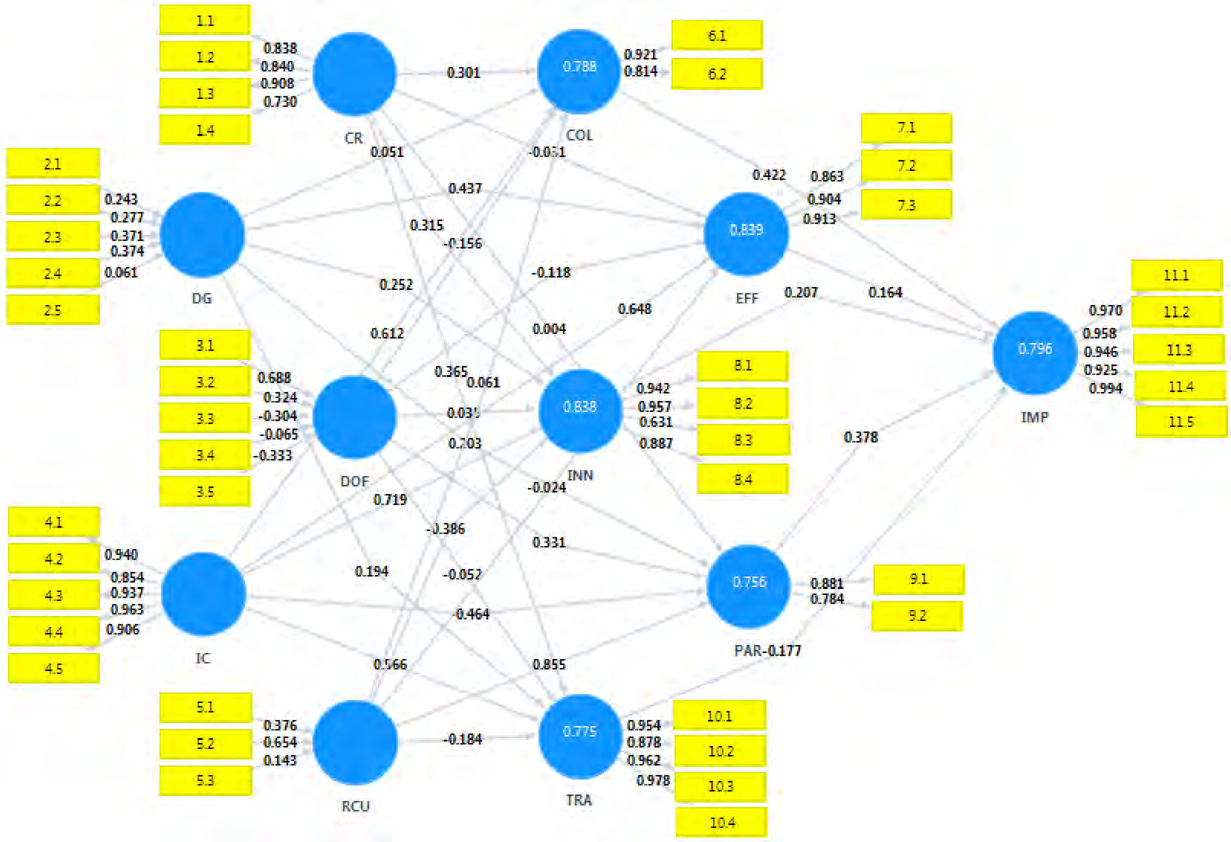
Given that highly skewed data inflate bootstrap standard errors [4], thus statistical Given that highly skewed data inflate bootstrap standard errors [4], thus statistical parameters of kurtosis and skewness were calculated using the Data Analysis tool in Microsoft Excel. There were no missing data and all columns showed a reasonable degree of normality (kurtosis < |1.5|, skewness <|1|) except for International Internet bandwidth (bit/s) per Internet user, Secure Internet servers per one million people, The Patent Cooperation Treaty patent applications and GDP per capita where it was 2.7, 2.1, 2.5 and 1.6 respectively, which was solved by converting these attributes to a logarithmic scale, because there were no negative numbers. Then, the dataset was converted into .csv file format and uploaded into SmartPLS. Here, the inner model of latent variables was built. Then, the outer model was built by linking the indicators to the related latent variable. When formative indicators exist in the model, the direction of the arrows has to be reversed. That is, the arrow should be then pointing from the formative indicators to the latent variable in SmartPLS.

Reporting the precise settings is important, because a poor choice of options can lead to significantly biased standard error estimates [11]. Therefore, settings of the PLS algorithm were configured with these parameters – weighting scheme: path weighting scheme; maximum iterations: 500; stop criterion: 10^-7 and initial weights: 1.0. All measures were also standardized before running the algorithm. SmartPLS can generate T-statistics for significance testing of both the inner and outer model, using a procedure called bootstrapping. In this procedure, a large number of subsamples (e.g., 5000) are taken from the original sample with replacement to give bootstrap standard errors, which in turn gives approximate T-values for significance testing of the structural path. The Bootstrap result approximates the normality of data [16]. Then, settings were configured with these parameters – subsamples: 5000; test type: two tailed; significance level: 0.05 and sign changes: no sign changes.

4 Results and discussion

In the PLS-SEM diagram, which can be seen from the Fig. 2, there are two types of numbers – numbers in the circle: these show how much the variance of the latent variable is being explained by the other latent variables; and numbers on the arrow, which are called the path coefficients and explain how strong the effect of one variable is on another variable. The weight of different path coefficients enables to rank their relative statistical importance [16].

Fig. 2: The PLS-SEM diagram with the results



Source: Authors

By looking at the diagram, the following preliminary observations can be made. The coefficient of determination (R^2) is 0.796 for the target IMP endogenous latent variable. For R^2 of 0.75 it is substantial, 0.50 is moderate, and 0.25 is weak [5], [16]. This means that the five endogenous latent variables (COL, EFF, INN, PAR and TRA) substantially explain 79.6% of the variance in IMP, which is also 5% more than in the study [7]. The exogenous latent variables then substantially explain 78.8 % of the variance in COL, 83.9 % in EFF, 83.8 % in INN, 75.6% in PAR and 77.5 % in TRA. The inner model suggests that COL has the strongest effect on IMP (0.422), followed by PAR (0.378) and INN (0.207). Therefore, it can be concluded that COL and PAR are both moderately strong predictors of IMP.

One of the concerns with formatively measured constructs is multicollinearity across the attributes of each construct. High first eigenvalues can be an indicator of multicollinearity, however, all formative construct´s first eigenvalues are lower than 3. All Variance Inflation Factors (VIFs) were also below the recommended 5.00 value [5]. Table 2 then presents the reliability and validity of the latent variables (reflective outer model) to complete the examination of the inner structural model.

Tab. 2: Results summary for reflective outer model

Latent variable	Indicators	Loadings	Indicator reliability	Composite reliability	Cronbach's alpha	AVE
CR	1.1	0.838	0.702	0.899	0.849	0.691
	1.2	0.840	0.706			
	1.3	0.908	0.824			
	1.4	0.730	0.533			
IC	4.1	0.940	0.884	0.965	0.955	0.848
	4.2	0.854	0.729			
	4.3	0.937	0.878			
	4.4	0.963	0.927			
	4.5	0.906	0.821			
COL	6.1	0.921	0.848	0.860	0.687	0.755
	6.2	0.814	0.663			
EFF	7.1	0.863	0.745	0.922	0.874	0.799
	7.2	0.904	0.817			
	7.3	0.913	0.834			
INN	8.1	0.942	0.887	0.920	0.881	0.747
	8.2	0.957	0.916			
	8.3	0.731	0.534			
	8.4	0.887	0.787			
PAR	9.1	0.881	0.776	0.820	0.668	0.695
	9.2	0.784	0.615			
TRA	10.1	0.954	0.910	0.970	0.959	0.891
	10.2	0.878	0.771			
	10.3	0.962	0.925			
	10.4	0.978	0.956			
IMP	11.1	0.970	0.941	0.983	0.978	0.919
	11.2	0.958	0.918			
	11.3	0.946	0.895			
	11.4	0.925	0.856			
	11.5	0.994	0.988			

Source: Authors

Indicator reliability (i.e. loadings^2), measured as outer loadings numbers, 0.70 or higher is preferred. If it is an exploratory research, 0.40 or higher is acceptable [4], [5]. Internal consistency reliability, measured as composite reliability and also Cronbach's alpha, should be 0.70 or higher. If it is an exploratory research, 0.60 or higher is acceptable. Convergent validity, measured as average variance extracted (AVE), can be accepted when the value is greater than 0.50 [4], [11]. Otherwise, these indicators should be removed from the measurement model, since they indicate that the selected indicators have less contribution towards the related constructs [1], [5]. This procedure is known as unidimensionality procedure [1]. This model assessment should be applied in order to improve model's reliability and validity. However, in this model, all the requirements are achieved. Then, the discriminant validity was conducted.

Discriminant validity (as Fornell-Larcker criterion) values were obtained from the square root of AVE value and are shown in the Table 3. The diagonal values (in bold) are the square root of AVE, while the other values are the correlations between the related constructs. In this case, the discriminant validity is achieved when a diagonal value is higher than the value in its row and column [1]. The result then indicates that discriminant validity is well established.

Tab. 3: Fornell-Larcker criterion analysis for checking discriminant validity

Latent variable	CR	IC	COL	EFF	INN	PAR	TRA	IMP
CR	**0.831**							
IC	0.818	**0.921**						
COL	0.823	0.861	**0.869**					
EFF	0.817	0.891	0.792	**0.894**				
INN	0.808	0.890	0.758	0.861	**0.864**			
PAR	0.755	0.788	0.611	0.768	0.700	**0.834**		
TRA	0.806	0.857	0.825	0.886	0.845	0.681	**0.944**	
IMP	0.804	0.920	0.794	0.811	0.784	0.787	0.749	**0.959**

Source: Authors

Using a two-tailed t-test with a significance level of 5%, the path coefficient will be significant if the T-statistics is larger than 1.96 [5], [16]. This has to be done for the path coefficients of the inner model, which are shown in the Table 4, as well as for the outer model, where all of the T-statistics are larger than 1.96, so it can be said that the outer model loadings are highly significant. In the case of the inner model, it can be claimed that only the COL – IMP, INN – IMP and the PAR – IMP linkage are significant in the context of this study. This also confirms the earlier findings. Also the IC exogenous latent variable has the significant impact on all the endogenous latent variables.

Tab. 4: T-statistics of path coefficients (inner model)

Relationship	T-statistics	Result	Relationship	T-statistics	Result
CR → COL	2.045	Significant	IC → COL	3.043	Significant
CR → EFF	0.228	Not significant	IC → EFF	3.746	Significant
CR → INN	2.214	Significant	IC → INN	3.504	Significant
CR → PAR	0.027	Not significant	IC → PAR	2.060	Significant
CR → TRA	2.822	Significant	IC → TRA	2.503	Significant
DG → COL	0.423	Not significant	RCU → COL	0.344	Not significant
DG → EFF	4.208	Significant	RCU → EFF	0.180	Not significant
DG → INN	2.399	Significant	RCU → INN	2.664	Significant
DG → PAR	1.779	Not significant	RCU → PAR	4.073	Significant
DG → TRA	1.465	Not significant	RCU → TRA	0.879	Not significant
DOF → COL	2.196	Significant	COL → IMP	4.191	Significant
DOF → EFF	1.560	Not significant	EFF → IMP	1.213	Not significant
DOF → INN	0.403	Not significant	INN → IMP	1.982	Significant
DOF → PAR	3.293	Significant	PAR → IMP	4.073	Significant
DOF → TRA	0.607	Not significant	TRA → IMP	1.505	Not significant

Source: Authors

Conclusion

The purpose of the proposed model was to demonstrate the impact of open data and how governments can improve their actions by understanding the relationships among the related enabling factors and generating mechanisms. It provides a more systematic approach to measure the role of open data in improving collaboration, participation, innovation, transparency and efficiency of governments. The results suggest that the focus should be on the support of collaboration, participation and innovation generating mechanisms. They also show that the five endogenous latent variables (COL, EFF, INN, PAR and TRA) used in this model substantially explain 79.6% of the variance of the open data impact (IMP). The most significant indicators in the impact construct are social and economical impact, i.e. open data have the biggest impact on these two areas. These findings would result in more confident predictions and evaluations of open data impacts using constructs introduced in the newly proposed model.

This model represents the most important scientific contribution of this paper, because it is consisted of the most recent attributes defining actions and trends in the e-government development focusing on open data. This model can be also easily extended in the future.

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