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Towards an Open Data-adapted Innovation Resistance Theory**

Nikiforova, Anastasija; Zuiderwijk, Anneke

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Barriers to Openly Sharing Government Data: Towards an Open Data-adapted Innovation Resistance Theory

Anastasija, AN, Nikiforova

University of Tartu, Faculty of Science and Technology,
Tartu, Estonia

Nikiforova.Anastasija@gmail.com

Anneke, AZ, Zuiderwijk

Delft University of Technology, Faculty of Technology,
Policy and Management, Delft, Netherlands

a.m.g.zuiderwijk-vaneijk@tudelft.nl

ABSTRACT

Open Government Data (OGD) is a fundamental source for sustainability-oriented and data-driven innovation by citizens, companies, and other actors. However, many government agencies are reluctant to openly share their data with the public. While the resistance of public organizations to openly share government data has been investigated in previous research, most of these studies are focused on the reuse of open government data by companies and citizens. There is a paucity of research applying theoretical models to study the provision of OGD, and more specifically, the resistance of public organizations to make government data publicly available. We argue that Innovation Resistance Theory (IRT), which considers both functional and psychological factors, can be used to study OGD barriers, where OGD is seen as a source of innovation. This study aims to develop an OGD-adapted IRT model to empirically identify predictors affecting public agencies' resistance to openly sharing government data. Based on a review of the literature on both IRT research and barriers associated with open data sharing by public agencies, we develop an initial version of the model. In our future research, we plan to conduct exploratory interviews in multiple countries to refine the model. Ultimately, we will validate the refined model to study the resistance of public authorities to openly sharing government data in a quantitative study.

CCS CONCEPTS

• **Government technology policy**; • **Computing / technology policy**; • **Social and professional topics**;

KEYWORDS

Open Government Data, Innovation Resistance Theory, Open data, OGD, Barrier

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1 INTRODUCTION

Open Government Data (OGD) is considered an essential source for sustainability-oriented and data-driven innovation by citizens, companies, researchers, and public organizations [1–3]. OGD are structured, machine-readable data that governments collect and actively publish on the internet with the aim to have the data freely reused by the public without restrictions [4–6]. Using OGD, companies are expected to create new, innovative products and services [2, 3]. Moreover, researchers may use publicly available data to combine various datasets, test new hypotheses, develop models (e.g., the SARS-CoV-2 transmission model [7]) and derive ground-breaking insights [8–10]. Furthermore, public organizations may reuse other public agencies' OGD, which could stimulate collaboration and knowledge exchange [11, 12].

In the past two decades, research on OGD has started to thrive. In particular, many studies on the drivers and inhibitors for the adoption of OGD have been conducted [e.g., 2,3], both from the data providers' and data users' perspectives. From the data user perspective, the acceptance of OGD by different user types has been investigated using various theoretical models. For example, the Technology Acceptance Model (TAM) has been used to examine the determinants of OGD use [13], the Unified Theory of Acceptance and Use of Technology (UTAUT) has been used to study the behavioural intention to accept and use OGD in different countries (India, Czech Republic, Latvia, Bangladesh) [14–16], and gamification theory has been applied to examine how playful interfaces can help tailor OGD portals for lay citizens [17]. Several other studies focused on the perspective of the OGD provider, i.e., the public organizations, in their resistance to openly sharing government data. For example, Wang & Lo [18] used the Technology–Organization–Environment (TOE) to investigate factors influencing the adoption of OGD among government agencies and Hossain et al. [19] proposed a model that incorporates seven context-specific TOE variables to understand the underlying factors that influence OGD initiatives.

Although various studies have applied theoretical models to investigate open data, most of them are focused on the reuse of these data by companies and citizens e.g., [13, 20]. There is a paucity of research applying theoretical models to study the provision of OGD, and more specifically, the resistance of public organizations to make government data publicly available. Moreover, most studies on OGD barriers were carried out before the COVID-19 pandemic. However, previous research on OGD in relation to COVID-19 suggests that the pandemic affected the mind-set of citizens, researchers, and governments on the role of OGD and the benefits of these data for these stakeholders [9, 10, 21, 22]. Previous research suggests that the behavioural patterns of both OGD users and, more importantly, OGD providers may have changed their attitude towards OGD,

perhaps moving towards a more open paradigm. At the same time, several new issues were identified because of a more scrupulous analysis of data being opened by public agencies and their value [9]. Therefore, new insights might be gained through an OGD barrier study conducted after the COVID-19 pandemic.

One theory that may particularly be valuable to studying barriers to OGD provision is Innovation Resistance Theory (IRT). This theory, developed by Ram & Sheth [23], claims that resistance to innovation depends on three sets of factors that lead to adoption, rejection, or modification of innovation if it is amendable to changes. It considers both functional and psychological (sometimes called behavioural) barriers. **Functional barriers** refer to “*product usage patterns, product value, and risks associated with product usage*” [23, p.7] and usually arise if consumers face significant changes from adopting the innovation, where we assume that data publishers can be considered as customers to some extent. **Psychological barriers** arise due to (1) the traditions and norms of the customer and (2) the perceived product image as a result of conflict with the previous beliefs of customers. The division into functional and psychological barriers allows IRT to explore both active resistance by means of functional barriers proposed by IRT, while psychological barriers refer to the analysis of passive resistance. Previous OGD barrier research reveals the importance of factors in both categories [15]. This study aims to develop an OGD-adapted IRT model to empirically identify predictors affecting public agencies’ resistance to openly sharing government data. Based on a literature overview of both IRT research and barriers associated with data opening by public agencies, we develop an initial version of the model, which we plan to refine in future research.

Throughout the entire paper, we use the terms OGD, openly sharing government data, government data openness, and government data sharing interchangeably.

2 BACKGROUND AND RELATED WORK

In this section, we provide a background on IRT and barriers to openly sharing government data. This should constitute the input to our OGD-adapted IRT model, which will use the IRT as a theoretical framework.

2.1 Innovation Resistance Theory

Resistance to change was defined by Zaltman and Wallendorf [24] as “*any conduct that serves to maintain status quo in the face of pressure to alter the status quo*”. According to Ram [25], it is associated with the degree to which individuals feel threatened because of the need to make changes to the typical process of doing something. Innovation Resistance Theory was initially proposed by Ram [25]

and then modified in 1989 [23] as a special version of ‘*resistance to change*’ widely discussed in (social) psychology in behavioural science concluding that resistance is a normal response of consumers when faced with innovation. More precisely, consumers experience resistance to changes imposed by innovation to the extent that they may suffer from changes that affect the typical process of obtaining information, purchase, use or dispose of new products. The main claim of IRT is that resistance to innovation depends on three sets of factors that lead to one of three – adoption, rejection, or modification of innovation, if it is amendable to changes. These factors are (1) **perceived innovation resistance**, which may be (a) **consumer dependent** and (b) **consumer independent** (e.g. trialability, divisibility, communicability, reversibility), (2) **consumer characteristics** – (a) **psychological variables** and (b) **demographics variables**, (3) **propagation mechanism** divided into (a) **type**, e.g., marketer controlled vs. non-marketer controlled, personal vs. impersonal, and (b) **characteristics** described by clarity, credibility, source similarity and informativeness. The decision on the adoption is achieved by considering both functional and psychological barriers, where Ram and Sheth [23] categorize functional barriers into product (1) **usage** patterns, (2) **value**, and (3) **risks** associated with its usage. These barriers are typically caused by significant changes that consumers face when adopting an innovation. Psychological barriers, however, arise due (1) **traditions** and norms of the customer and (2) the perceived product **image** because of conflict with the previous beliefs of customers (Table 1). In the light of the above, and given the specificity of the OGD nature, we assume that not only end-users, but also data publishers can be considered as customers to some extent.

To identify relevant literature in which IRT was the primary research object, we conducted a systematic literature review (SLR) by searching Scopus and Web of Science (WoS). We queried these databases using the keywords (“*Innovation Resistance Theory*” OR (“*IRT*” AND “*innovation*” AND “*resistance*”)) in the search item’s title, keywords, and abstract. We only considered English peer-reviewed papers and book chapters. This search resulted in 52 articles in Scopus and 34 in WoS. After comparing the results and eliminating duplicates, 54 studies remained for their further examination.

The search results reveal that a vast majority of scholars used the IRT as the basis for the empirical evaluation of consumer resistance to innovations [30]. Huang et al. [31] found that digital financial services such as mobile payments, mobile banking, and e-commerce, including mobile social commerce, mobile website shopping, online shopping, are the two main research contexts for

Table 1: The Innovation Resistance Theory (IRT) model and its elements.

Resistance factors	Resistance sub-factors	Definition and source
Functional Barriers	Usage Barrier	The degree to which an innovation is perceived as requiring changes in consumers’ routines [23, 26]
	Value Barrier	The degree to which an innovations’ value-to-price ratio is perceived in relation to other product substitutes [26, 27]
	Risk Barrier	The degree of uncertainty in regard to financial, functional, and social consequences of using an innovation [26, 28]
Psychological Barriers	Tradition Barrier	The degree to which an innovation forces consumer to accept cultural changes [26, 29]
	Image Barrier	The degree to which an innovation is perceived as having an unfavorable image [23, 26]

IRT-applications. Our search results confirm this finding [32–35]. Huang et al. [31] found that there is a growing focus on food innovations such as organic food [36], the internet of things [37], and the collaborative consumption or sharing economy [26]. Huang et al. [31] and Talwar et al. [30] emphasize the need for the exploration of innovation resistance in emerging trends, which can be associated with some degree of risk or uncertainty, especially with regard to cutting-edge innovations such as Artificial Intelligence, smart services, genetic engineering techniques, 5G, virtual and augmented reality, blockchain, cryptocurrencies, and innovations that are associated with social and environmental benefits. Although IRT is rather domain-agnostic, it allows and even requires adaptations to the concerned topic and its specificities not only in terms of defining measurement items constituting the model but also their list and nature and, in some cases, even in relation to barriers. As an example, Leong et al. [35] investigated a consumer resistance to mobile wallet adoption extending the IRT model with “perceived novelty” and “mobile wallet resistance”, and socio-demographic variables such as education, age, and income. This allowed them to find significant effects of education, usage barrier, risk barrier, value barrier, tradition barrier, and perceived novelty on m-wallet innovation resistance, but not for age, income, and image barriers. Ma et al. [38] investigated the barriers to the use of MOOCs, where the “individual level barrier” including self-control and attitude with reference to “procrastination”, “distraction” and “concentration”, and “environmental level barrier” with reference to “promotion” and “circumstance” extended the IRT model. Several other scholars also adapted the IRT model to make it better fit the context of their research [34, 39–42]. In some cases, IRT is also used in combination with other theories

such as TAM [40], UTAUT framework [32, 44–46], and Distrust Theory [40]. Our literature review suggests that most studies using IRT adopt a quantitative approach, while the number of qualitative studies applying IRT is limited to a few exceptions (e.g., [38, 47, 48]).

2.2 Barriers to openly sharing government data

Previous studies already identified various types of barriers to openly sharing government data, which we assume can lead to resistance in OGD adoption. Table 2 presents these barriers in the IRT barrier categories.

3 OGD-ADAPTED INNOVATION RESISTANCE MODEL

IRT suggests to define five hypotheses, one for each barrier type, and to test and validate those using quantitative research (see Figure 1). Each hypothesis is developed as “[Construct ∈ {Usage barrier; Value Barrier; Risk barrier; Tradition Barrier; Image Barrier}] has a positive effect on public agencies’ resistance toward openly sharing government data”.

Table 3 provides the measurement items for each of the five hypotheses depicted in Figure 1. We defined the measurement items by drawing from existing IRT models and the corresponding measurement items found in the literature (Section 2.1), combined with the insights obtained on OGD-specific barriers (Section 2.2). In total 36 measurement items were defined.

We will refine and validate these measurement items in a round of interviews with public agencies. We expect that the validation interviews will also provide more insight in possible control variables

Table 2: Examples of barriers to openly sharing government data that can lead to resistance.

Resistance sub-factors	Examples of barriers to openly sharing government data, leading to resistance
Usage barriers	OGD often suffer from quality issues [9, 15, 21] Openly sharing government data is a complicated process [49] Open government data portals suffer from low ease of use [50] Insufficient user-friendliness of the data [51]
Value barriers	Open government data do not always provide value to users [52] Datasets may be incomplete [15, 53, 55] There may be concerns about the quality of open data [9, 15, 21, 51,54,56–58] Openly sharing government data requires resources, including time and costs [12, 55, 59] Impossible to sell the data when it is openly available [51, 60] Data providers are usually the ones who invest the most effort and time in publishing data, while businesses and citizens as data users profit the most [52]
Risk barriers	Organizations’ fear that openly shared government data will be misused [52] Organizations’ fear of open data users drawing false conclusions [49, 60] Organizations fear that (privacy) sensitive data will be shared openly [49, 51, 55, 57, 58, 61] Organizations fear making mistakes when preparing data for publication [53] Organizations fear being liable for data quality [49,54,55]
Tradition barriers	The risk-averse culture of governmental organizations avoids openly sharing the data [58, 62] Organizations are reluctant to change their processes [12, 60,61] Incompatible routines and processes of organizations [12,61] Civil servants may lack the skills required for openly sharing government data [12,61,63]
Image barriers	Organizations’ fear that their reputation will be damaged due to the publication of low-quality data [53] Organizations’ fear that they will be associated with incorrect conclusions drawn from OGD analysis [53]

Table 3: The OGD-adapted Innovation Resistance Theory (IRT) model and its elements.

Barrier	Measurement item
Usage	UB1: It is difficult to attain the appropriate quality level for open government data to be shared openly
Barrier	UB2: It is difficult to prepare data for publication so that they comply with OGD principles
(UB)	UB3: It is difficult to prepare data for publication so that they become appropriate for reuse
	UB4: Data are difficult to publish on the OGD portal due to the complexity of the process
	UB5: Data are difficult to publish on the OGD portal due to the unclear process
	UB6: Data are difficult to publish on the OGD portal due to their limited functionality
	UB7: Open government data portals often do not allow for semi-automation of the publishing process
	UB8: It is difficult to maintain openly shared government data
Value	VB1: My organization believes that openly sharing government data is often not valuable for the public
Barrier	VB2: Many open government datasets are not appropriate for reuse
(VB)	VB3: Many open government datasets suffer from data quality issues (completeness, accuracy, uniqueness, consistency etc.)
	VB4: The public gains of openly sharing government data are often lower than the costs
	VB5: My organizations' gains of openly sharing government data are often lower than the costs
	VB6: Data preparation is too resource-consuming for my organization
	VB7: Open government data do not provide any value to my organization
	VB8: Open data that my organization can openly share will not provide value to users
	VB9: The amount of resources to be spent to prepare, publish and maintain open government data outweigh the benefit my organization gains from it
Risk	RB1: My organization fears the misuse of openly shared government data
Barrier	RB2: My organization fears the misinterpretation of openly shared government data
(RB)	RB3: My organization fears that openly shared government data will not be reused
	RB4: My organization fears violating data protection legislation when openly sharing government data
	RB5: My organization fears that sensitive data will be exposed as a result of opening its data
	RB6: My organization fears making mistakes when preparing data for publication
	RB7: My organization fears that users will find existing errors in the data
	RB8: My organization fears that openly sharing its data will reduce its gains (otherwise the organization could sell the data or use it in another beneficial way)
	RB9: My organization fears that openly sharing its data will allow its competitors to benefit from this data
Tradition	TB1: Freedom of information requests are sufficient for the public to obtain government data
Barrier	TB2: My organization is reluctant to implement the culture change required for openly sharing government data
(TB)	TB3: Employees in my organization lack the skills required for openly sharing government data
	TB4: Employees in my organization lack the skills required for maintaining openly shared government data
	TB5: My organization is reluctant to radically change the organizational processes that would enable openly sharing government data
Image	IB1: My organization has a negative image of open government data
Barrier	IB2: My organization believes that open government data is not valuable for users
(IB)	IB3: My organization fears that openly sharing government data will damage the reputation of my organization
	IB4: My organization fears that the accidental publication of low-quality data will damage the reputation of my organization
	IB5: My organization fears that associating them to incorrect conclusions drawn from OGD analysis by OGD users will damage the reputation of my organization

that need to be included, such as organization size, the existence of OGD legislation and policies, and the available funding.

4 CONCLUSIONS AND FUTURE WORK

This study aims to develop an OGD-adapted IRT model to empirically identify predictors affecting public agencies' resistance to openly sharing government data. Based on the literature review concerning both IRT research and barriers associated with open data sharing by public agencies, we develop an initial version of the model. Compliant with the IRT literature, our conceptual model consists of five main constructs, including user barriers, value barriers, risk barriers, tradition barriers, and image barriers. Based on these barriers we defined five hypotheses to study the resistance of public authorities to openly share government data. For each of these constructs, we defined a list of measurement items specific

to the context of OGD. This study is conceptual, and we did not validate the created model yet. In our future research, we plan to refine the model by conducting exploratory interviews in countries with different maturity levels of OGD initiatives. Ultimately, we will validate the refined model in a quantitative study of public agencies' resistance to OGD provision. Considering the context of this model and the current rise in popularity of the Business-to-Government (B2G) data sharing, in light of which the European Commission is taking regulatory action and is preparing the Data Act to set the rules and conditions, thereby changing the current voluntary model to a more mandatory data sharing [65], we believe that the proposed model can become a reference model to analyse predictors affecting resistance to share data in this subdomain.

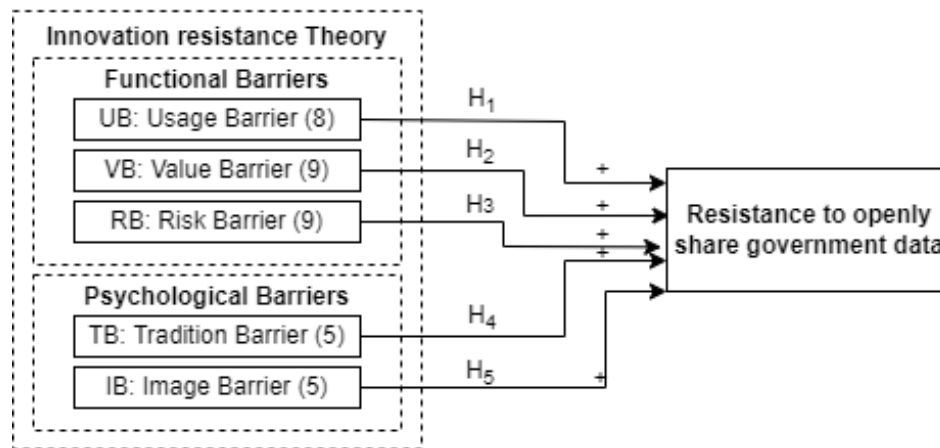


Figure 1: Research model and proposed hypotheses (the numbers in brackets refer to the number of measurement items in Table 3)

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