

## Do open government data (OGD) portals show signs of knowledge management (KM) practices?

### an empirical investigation

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**DOI**

[10.1080/09537325.2023.2280512](https://doi.org/10.1080/09537325.2023.2280512)

**Publication date**

2024

**Document Version**

Final published version

**Published in**

Technology Analysis and Strategic Management

**Citation (APA)**

Paterne Chokki, A., Alexopoulos, C., Matheus, R., Saxena, S., Frénay, B., & Vanderose, B. (2024). Do open government data (OGD) portals show signs of knowledge management (KM) practices? an empirical investigation. *Technology Analysis and Strategic Management*, 36(12), 4829-4844. <https://doi.org/10.1080/09537325.2023.2280512>

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# Do open government data (OGD) portals show signs of knowledge management (KM) practices?: an empirical investigation

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## ABSTRACT

Open Government Data (OGD) is a build-up of the data accumulated in the government organisations pertaining to the structural and functional dimensions and it is imperative for OGD to be high-value for facilitating value creation and innovation. The present study purports to provide a launchpad to the aforementioned truism by advancing the concept of Open Government Data Capital (OGDC) resting on the principles of Knowledge Management (KM) given that the high-value OGD can result only with the engagement of the concerned administrative agencies in knowledge sharing for being made accessible for wider use via dedicated web portals. To drive home the arguments, an empirical investigation is conducted with four top-notch countries, viz., Canada, Australia, New Zealand and the United States, in terms of the quantitative evaluation of their OGD portals' quality and inferences are drawn as to how OGDC may be furthered with the provision and maintenance of high-value datasets. Thus, it is shown that the Australian OGD portal is qualitatively robust and leads in terms of OGDC which may be beefed up with more integration of the KM practices in terms of the inter-governmental agencies' coordination and the other countries are lagging behind in terms of the quality parameters.

## ARTICLE HISTORY

Received 20 April 2023  
Revised 5 September 2023  
Accepted 31 October 2023

## KEYWORDS

Open government data (OGD); open government data capital (OGDC); quality; knowledge management

## 1. Introduction

Open Government Data (OGD) pertains to the provision of high-value datasets pertaining to the structural and functional facets of administrative bodies via dedicated web portals for facilitating the re-use of the same by a range of stakeholders to further value creation and innovation (Jetzek, Avital, and Bjorn-Andersen 2014; Peled 2011; Wirtz, Weyerer, and Rosch 2018). OGD is considered as datasets but it needs to be appreciated that without the linking of datasets, meaningful interpretation cannot be done (Kalampokis, Tambouris, and Tarabanis 2011; Muñoz, Bolívar, and Arellano 2022; Shadbolt et al. 2012) and this implies that knowledge creation-the resultant OGD repositories – happens and this OGD assumes form as an Open Government Data Capital (OGDC) which is further processed into valuable outputs thereby leading to value creation and innovation. OGDC happens when there is a high-value OGD sourced from different sources such that inter-governmental agencies coordinate with one another in this process of knowledge sharing, and, hence, knowledge creation. Thus, in the present study, OGDC is defined as: ‘the holistic OGD which gets

accumulated in the public web repositories as “knowledge warehouse” and is transmuted into valuable information for value creation and innovation’. Knowledge Management (KM) includes ‘knowledge acquisition, encoding, storage, transfer, application and sharing’ (Zhao et al. 2021, 372). In the context of OGD, knowledge sharing assumes significance on account of the involvement of different government departments and even other stakeholders where the citizens become the contributors to the OGD repositories—case in point being the users themselves who engage in knowledge exchange with the OGD providers and this goes a long way in OGD quality improvisation besides serving as a feedback-and-control apparatus (Ruijter and Meijer 2020). The chief impediment towards OGDC is linked with the quality of OGD per se (Sadiq and Indulska 2017). Therefore, knowledge handling strategies assume criticality with the technical infrastructure in place and the requisite personnel acknowledging their responsibilities (Lai et al. 2021; Rhee and Choi 2017) in administrative organisations so that datasets are provided in complete and accurate formats via the dedicated web portals.

But for touching base on the manner in which knowledge sharing happens via linked OGD (Davies and Edwards 2012), there has been scant academic attention on the fact that organisational factors play a significant role in knowledge sharing in the public sector (Welch, Feeney, and Park 2016; Zhang, Dawes, and Sarkis 2005) but the same has not been appreciated in the domain of OGD: the present study seeks to plug this gap in two ways: 1. It provides a brief regarding the need for knowledge management (KM) vis-a-vis OGD, and 2. It provides an empirical investigation regarding the knowledge management of four out of top-10 countries ranked across OGD initiatives given that without quality maintenance, knowledge management cannot happen. The research question addressed by the study is: ‘To what extent is KM furthered across the OGD portals in countries faring well in the OGD initiatives’ standards?’ As a theoretical contribution to the extant KM literature wherein the impetus upon knowledge sharing practices has been forwarded to result in increased knowledge corpus creation via value derivation and innovation, the present study hinges itself in line with the assertion that ‘knowledge management representation systems have been created and continue evolving in order to link different data’ (Charalabidis, Alexopoulos, and Loukis 2016, 48), the present study addresses the call made by Charalabidis and his colleagues that further research is warranted in the ‘integrated knowledge base’ domain vis-a-vis OGD.

The rest of the paper is structured as follows: following a brief on the implications of OGD for knowledge management and the creation of OGDC (Section 2), the research methodology is detailed (Section 3) with the results (Section 4) and the discussion of the findings (Section 5) and conclusion is provided (Section 6) with a rounding off with the indications for future research veering around OGDC (Section 7).

## 2. Literature review

Fundamentally, ‘data can be seen as the lowest level of abstraction from where information and then knowledge are derived’ (Ubaldi 2013, 5) and as far as the OGD initiatives are concerned, it is important that ‘co-development of knowledge’ happens by the ‘encouraging external inputs and new sources of knowledge’ (Ubaldi 2013, 14). Besides formulating a long-drawn strategy and capable leadership, a sustainable OGD initiative mandates that its OGD initiative is well-entrenched alongside the ‘necessary coordinations with other agencies’ (Solar, Concha, and Meijueiro 2012, 214). Inter-departmental coordination and integration is significant for ensuring that data is shared across the departments for furthering knowledge sharing (Dawes 2012; Sanderson et al. 2015; Zhao et al. 2022) and making it available on the dedicated portals for public re-use. This coordination is impeded on account of several reasons, for instance, the perceived risk and hierarchical organisation, bureaucratic and autocratic decision-making culture (Wirtz et al. 2016). In the empirical study conducted on the Taiwan government agencies’ OGD initiatives, it was shown that governments must engage in data exchange for the success of the OGD initiatives

given that they stand to gain in terms of the potential advantages of the OGD initiatives (Wang and Lo 2016). Thus, it has been attested that OGD initiatives involve inter-departmental collaboration along with the support from the senior management executives and the persistence of the personnel at the middle levels of management and the analysts (Krishnamurthy and Awazu 2016). This knowledge sharing culture among the organisations would result in OGDC: the repository created with the sharing of datasets pertaining to the administrative agencies which is replete in all aspects. OGDC is facilitative of open innovation via OGD by a range of stakeholders. Open innovation is furthered by the data-driven knowledge management and knowledge sharing endeavours (Chaston 2012; Del Vecchio et al. 2018). OGD engagement is instrumental in value derivation for entrepreneurial pursuits (Kitsios and Kamariotou 2023). Likewise, Open Social Innovation (OSI) involving the multitudinous stakeholders' engagement is linked with the extent to which the open platforms permit openness, accountability, resource availability and involvement (Fortunato et al. 2017; Gegenhuber et al. 2023). Also, given the possibilities of engaging in open innovation via open data, users engage in deriving nuances from visualisation and statistical analyses (Park and Gil-Garcia 2022).

However, OGDC can happen only when the OGD is high-value (Nikiforova 2021) and complete, accurate, updated, available in user-friendly formats like CSV, XLS that do not require any specialised software. The motivation to conceptualise OGDC was that in line with the extant research which is replete with instances where the OGD quality is a cause of concern (Grimmelikhuijsen and Feeney 2017; Martin, Rosario, and Pérez 2016; Matheus, Janssen, and Maheshwari 2020; Yang, Lo, and Shiang 2015), it becomes important for the government agencies to adopt a strategy for refurbishing the OGD initiative. For instance, in the case of the Czech Republic, it was deduced that the data catalogues are of low quality and that the OGD is scattered here and there and such haphazard implementation of the OGD initiative results in problems for the users in terms of data discovery and re-use (Kucera, Chlapek, and Necasky 2013). Six parameters for knowledge sharing quality pertain to the completeness, reliability, timeliness, relevance, ease of understanding and accuracy (Chiu, Hsu, and Wang 2006) and these dimensions constitute the sine qua non of OGD thereby clinching the main argument advanced in the present study. Thus, it is imperative to assess the quality of the OGD that is provided via the dedicated portals to understand if OGDC can be furthered with value creation and innovation by the stakeholders or not – the following section (Section 4) provides an initiation of this assertion.

### 3. Research methodology

Figure 1 summarises the different phases of the research methodology.

#### **3.1. Selection of country portals and determination of number of datasets to be analysed per portal**

To select the country portals to evaluate in this study, we rely on the Open Data Barometer (ODB), a well-acclaimed benchmark for OGD initiatives across countries in terms of their trajectories and progress over the years (World Wide Web Foundation 2018). The top 10 country portals ranked in the 2018 ODB report (Canada (CA), United Kingdom (GB), Australia (AU), France (FR), South Korea (KR), Mexico (MX), Japan (JP), New Zealand (NZ), United States (US), and Germany (DE)) are initially selected for further analysis. However, due to certain research considerations, we end up selecting only four (CA, AU, NZ, US) of these 10 top country portals. The research considerations are: (a) the interface, resources (i.e. the file containing the dataset) and metadata (i.e. the information about the dataset) in the portals should be in English, as most authors are not familiar with other languages, (b) the portals should provide an Application Programming Interface (API) to facilitate access to their datasets and metadata, (c) The resources on portals should be available in Comma Separated Values (CSV) format and well structured (e.g. no combination of metadata of columns

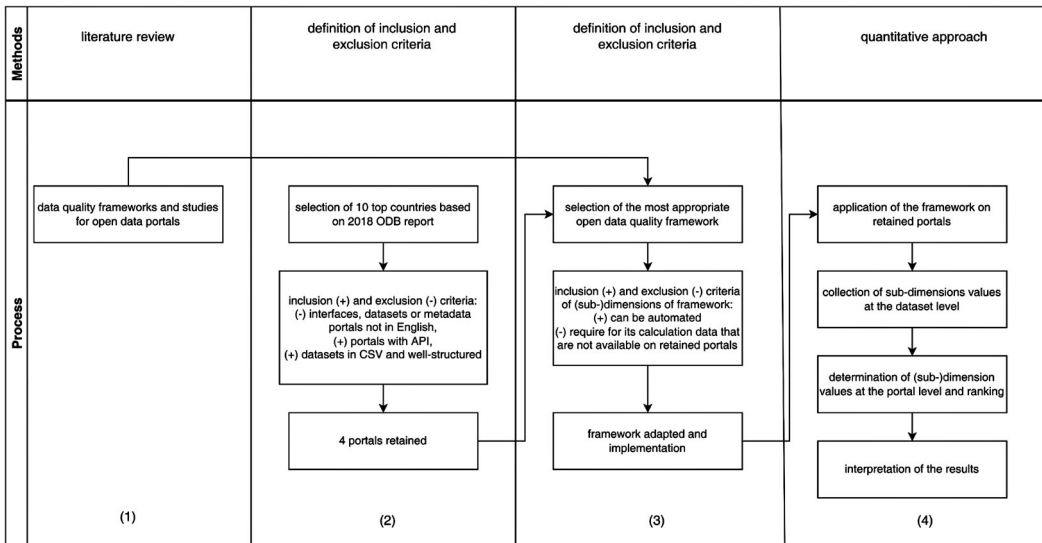


Figure 1. Research methodology.

and data in one single CSV file or existence of several empty rows in the CSV file as in the case of the GB portal) to facilitate automatic evaluation of the datasets.

Since there are thousands of CSV datasets for each portal and there is a restriction on the maximum number of data to be retrieved during a period on the portals, we decide to use a sample size of CSV datasets from each portal for the evaluation instead of the full CSV datasets. The formula below (Equation (1)) was used to determine the number of sample datasets ( $N'$ ) to collect in order to obtain statistically significant results from the initial number of CSV datasets ( $N$ ) (Alexander, Illowsky, and Dean 2017). The sample size for each portal was estimated at 600 datasets based on the following settings:  $p = 0.5$ ,  $e = 4\%$ , and  $z = 1.96$  (this value is obtained by considering a confidence interval of 95%). Table 1 presents the selected country portals with information on their access link, platform used to develop the portal, ODB rank (as of 2018), number of total CSV datasets (as of 20/10/2022).

$$N' = \frac{z^2 * p(1 - p)}{1 + \left( \frac{z^2 * p(1 - p)}{e^2 N} \right)} \tag{1}$$

Where  $p$  is the population proportion,  $N$  = total number of CSV datasets in the portal,  $e$  = margin of error,  $z$  = z-score.

Table 1. List of the country portals retained.

Country	ODB rank (2018)	Portal access link	Platform	Total number of CSV datasets ( $N$ ) as of 20/10/2022	Sample size ( $N'$ )
Canada (CA)	1	<a href="https://open.canada.ca">https://open.canada.ca</a>	CKAN	12,143	600
Australia (AU)	3	<a href="https://data.gov.au">https://data.gov.au</a>	MAGDA	11,117	
New Zealand (NZ)	8	<a href="https://data.govt.nz">https://data.govt.nz</a>	CKAN	16,126	
United States (US)	9	<a href="https://www.data.gov">https://www.data.gov</a>	CKAN	33,955	

### 3.2. Benchmarking framework

To assess the data quality of the retained portals, we have used the data quality framework proposed in (Vetrò et al. 2016). Since our goal in this study is to automate the data quality of the portals without the need to recruit participants, which is quite difficult (especially finding a significant number of open data experts for the evaluation) and time-consuming, we therefore determine which (sub-) dimensions of the selected framework need to be taken into account. Some inclusion and exclusion criteria are therefore proposed to achieve our goal. These are: (a) including all (sub-) dimensions that can be automated, i.e. that do not require the intervention of the participants in order to quantify them, and (b) excluding all (sub-) dimensions that rely on information not available on the evaluated portals. Applying these criteria, we retained four main dimensions (traceability, completeness, compliance, and accuracy). For example, the dimensions ‘currentness’ and ‘expiration’ were excluded because in most of the retained portals there is no record of previous versions of the datasets (resources), nor is there any information on the metadata of the previous updates of the datasets, the frequency of updates, and a complete list of updates dates (except the last update date). Table 2<sup>1</sup> lists all dimensions and sub-dimensions of the (Vetrò et al. 2016) framework with information on their description, formula or reason for exclusion when applicable (see grey rows for more detail about the excluded (sub-) dimensions). Once we identify the sub-dimensions to be automated, we then implement them in a python application (source code available at [https://github\\_url\\_available\\_after\\_review/](https://github_url_available_after_review/)). The implemented application is subdivided in four main steps:

- Random selection of 600 datasets from each portal. For each dataset, we download the associated CSV resources and metadata. Since there is a restriction on the number of data to be retrieved during a period on the portals, we decide to download a maximum of 10 resources per dataset and also limit the size of each resource to be downloaded to 200MB to prevent this error.
- Calculation for each dataset of the sub-dimensions: ‘Track of creation’, ‘Track of updates’, and ‘eGMS Compliance’. For each dataset, we rely on their metadata to calculate the values of the mentioned sub-dimensions.
- Calculation for each resource of the sub-dimensions: ‘Percentage of complete cells’, ‘Percentage of complete rows’, and ‘Percentage of accurate cells’. For the first two sub-dimensions, their calculations were straightforward. However, for the last sub-dimension ‘Percentage of accurate cells’, for each resource, we first detect the datatype of each column by enhancing the `csv_detective`<sup>2</sup> package (a python package that relies on regular expressions and column names to detect the datatype) in terms of regular expressions and supported datatypes. Then, we calculate the number of cells that have correct values according to the previously detected datatypes. The list of all 20 datatypes considered so far is as follows: address, country, country code, latitude, longitude, geo shape, geo point, Boolean, email, integer, float, image, phone, sex, url, colour, date, datetime (iso and rfc), hour and minute, year.
- Calculation for each dataset of the sub-dimensions: ‘Percentage of complete cells’, ‘Percentage of complete rows’, and ‘Percentage of accurate cells’. For each dataset, the values of these sub-dimensions are represented by the means of the values of the sub-dimensions of the related resources calculated in the previous step.

### 3.3. Data collection

Once the implementation of the automated framework is done, we then run the application on each of the four retained portals to collect 600 datasets for each of them. The data collections were performed on a Lenovo ThinkPad with 8 GB 2133 MHz RAM and 2.29 GHz Intel Core i5 CPU, running Windows 8.1. The runtime to collect the datasets for each portal was between 5 and 8 hours because for some datasets, the application needs to collect multiple resources (up to 10 resources) and some resources can be large files (up to 200 MB). For each portal, the application generates at the end of the run, a CSV file that includes information about the collected datasets (e.g. identifier,

**Table 2.** List of dimensions and sub-dimensions for the open data quality framework (adapted from Vetrò et al. 2016).

Dimension	Sub-dimension	Description	Variables and formula (normalised) or reason of exclusion
Traceability	Track of creation	Indicates the presence or absence of metadata associated with the process of creation of a dataset.	s: Source dc: Date of creation $tc = 2s + dc$ $tcn = tc/3$
	Track of updates	Indicates the existence or absence of metadata associated with the updates done to a dataset.	lu: List of updates du: Dates of updates $tu = lu + du$ $tun = tu/2$ <i>This metric is set to 0.25 since only the date of the last update is provided in the evaluated portals.</i>
Currentness	Percentage of current rows	Indicates the percentage of rows of a dataset that have current values, it means that they don't have any value that refers to a previous or a following period of time.	Impossible to retrieve resources from a previous period because a versioning module is not implemented in the evaluated portals.
	Delay in publication	Indicates the ratio between the delay in the publication (number of days passed between the moment in which the information is available and the publication of the dataset) and the period of time referred by the dataset (week, month, year).	No information on the frequency of updates and the dates of previous updates.
Expiration	Delay after expiration	Indicates the ratio between the delay in the publication of a dataset after the expiration of its previous version and the period of time referred by the dataset (week, month, year).	
Completeness	Percentage of complete cells	Indicates the percentage of complete cells in a dataset. It means the cells that are not empty and have a meaningful value assigned (i.e. a value coherent with the domain of the column).	nr: Number of rows nc: Number of columns ic: Number of incomplete cells ncl: Number of cells $ncl = nr * nc$ $pcc = (1 - ic/ncl) * 100$ $pccn = pcc/100$
	Percentage of complete rows	Indicates the percentage of complete rows in a dataset. It means the rows that don't have any incomplete cell.	nr: Number of rows nir: Number of incomplete rows $pcpr = (1 - nir/nr) * 100$ $pcprn = pcpr/100$
Compliance	Percentage of standardised columns	Indicates the percentage of standardised columns in a dataset. It just considers the columns that represent some kind of information that has standards associated with it (i.e. geographic information).	Impossible to automatically detect the standardised columns

(Continued)



**Table 2.** Continued.

Dimension	Sub-dimension	Description	Variables and formula (normalised) or reason of exclusion	
	eGMS compliance	Indicates the degree to which a dataset follows the e-GMS standard (as far as the basic elements are concerned, it essentially boils down to a specification of which Dublin Core metadata should be supplied)	s: Source dc: Date of creation c: Category t: Title d: Description (if applicable) id: Identifier (if applicable) pb: Publisher (if applicable) cv: Coverage (recommended only) l: Language (recommended only)	$egmsc = s + dc + c + t + 0.25 * (d + id + pb + l)$ $egmscn = egmsc/5$ This metric is adjusted because we exclude coverage (since it is only recommended and not available on the portals evaluated).
	Five star Open Data	Indicates the level of the five star Open Data model in which the dataset is and the advantage offered by this reason.	In this study, the value of this sub-dimension is set to 0.6 (3/5) since we only focus on CSV datasets.	
Understandability	Percentage of columns with metadata	Indicates the percentage of columns in a dataset that has associated descriptive metadata. This metadata is important because it allows to easily understand the information of the data and the way it is represented.	Unavailability and difficulty in automating the retrieval of metadata columns on the evaluated portals. Since, in some portals, the metadata and the dataset are in the same file and are not well structured.	
	Percentage of columns in comprehensible format	Indicates the percentage of columns in a dataset that is represented in a format that can be easily understood by the users and it is also machine-readable.	It is impossible to automate this sub-dimension. It requires human intervention to see if a column is understandable or not.	
Accuracy	Percentage of accurate cells	Indicates the percentage cells in a dataset that has correct values according to the domain and the type of information of the dataset.	nce: Number of cells with errors ncl: Number of cells	$pac = (1 - nce/ncl) * 100$ $pacn = pac/100$
	Accuracy in aggregation	Indicates the ratio between the error in aggregation and the scale of data representation. This metric only applies for the datasets that have aggregation columns or when there are two or more datasets referring to the same information but in a different granularity level.	Impossible to automate this sub-dimension. It requires human intervention to check if a column is an aggregation of other columns, since the names of the columns are often ambiguous.	

Grey rows are (sub-) dimensions not taking into account in this study.

title, description, publisher, creation date, etc.) and the values of the sub-dimensions: 'Percentage of complete cells', 'Percentage of complete rows', and 'Percentage of accurate cells'. Other sub-dimensions such as 'Track of creation' and 'eGMS compliance' are calculated using the excel formula since the information needed for their calculation has already been collected. The remaining sub-

dimensions ‘Track of updates’ and ‘Five star Open Data’ are set to 0.25 and 0.6, respectively, because for each dataset only the last update is provided (‘Track of updates’) and the format considered in this study is only CSV (‘Five star Open Data’).

All dimensions and sub-dimensions of the framework are weighted equally to facilitate comparison given the significance of all the dimensions and sub-dimensions. Thus, we calculate the value of each dimension for each dataset by computing an average across the sub-dimensions of the dimension. We also calculate the data quality for each dataset by calculating an average across the dimensions which would further an understanding of the extent to which the data are high-value. Once the (sub-) dimensions and data qualities are calculated for each dataset, we then calculate for each (sub-) dimension and data quality the means and the standard deviations (SD) in order to have an overview of these (sub-) dimensions and data quality at the portal level.

### 3.4. Interpretation of results

The results obtained in the previous section are then interpreted at three levels: (1) sub-dimension level, (2) dimension level and (3) portal level. For the sub-dimension level, we rely on the means and standard deviations calculated for each sub-dimension for each portal to compare the performance of the portals. For the dimension level, we use the means and standard deviations calculated for each dimension for each portal to compare portal performance. For the portal level, we look at the means and standard deviations calculated for data quality for each portal to compare the performance of the portals.

For each level, we also performed a T-test<sup>3</sup> and used the *p*-values generated by the T-test to determine whether there is a significant difference between the values of two portals. If the *p*-value  $\leq 0.05$ , then we conclude that there is a statistically significant difference. Otherwise, there is not enough evidence to state that there is a statistically significant difference.

## 4. Results

### 4.1. Results by sub-dimensions

Figure 2 shows the mean values by sub-dimension for the evaluated country portals. In order to confirm the higher score of one country portal compared to another portal, some statistical tests are performed and the results are summarised in Table 3. Regarding the sub-dimension ‘track creation’, all portals obtain an excellent score. These results show that all portals have provided the information about the data source and the creation date for each of their datasets. For the sub-dimension ‘track of updates’, all the portals have the same score and do not perform well. These scores can be justified by the fact that all portals do not provide the required information about

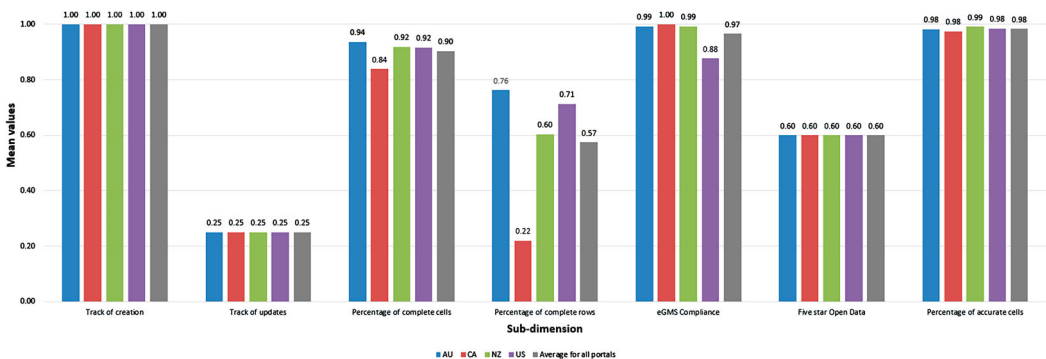


Figure 2. Mean values by sub-dimension for country portals.

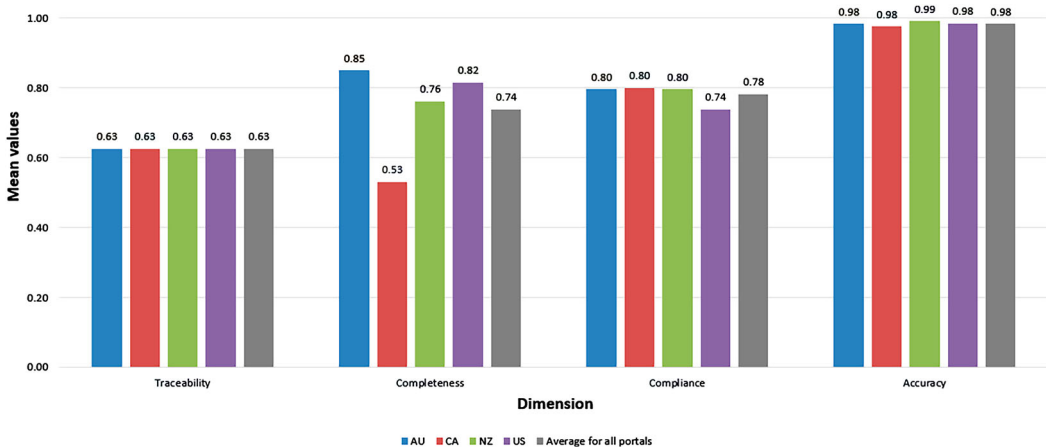
**Table 3.** Pairwise country portal comparisons by sub-dimension.

Sub-dimension	Pairwise country portal comparisons					
	AU-CA	AU-NZ	AU-US	CA-NZ	CA-US	NZ-US
Track of creation						
Track of updates						
Percentage of complete cells	(AU > CA)*	(AU > NZ)*	(AU > US)*	(NZ > CA)*	(US > CA)*	
Percentage of complete rows	(AU > CA)*	(AU > NZ)*	(AU > US)*	(NZ > CA)*	(US > CA)*	(US > NZ)*
eGMS Compliance	(CA > AU)*		(AU > US)*	(CA > NZ)*	(CA > US)*	(NZ > US)*
Five star Open Data						
Percentage of accurate cells		(NZ > AU)*		(NZ > CA)*		(NZ > US)*

Only statistically significant comparisons are shown. Star represents significance level: \* $p \leq 0.05$ .

their previous updates of their datasets, except the last modified date which is provided. For the sub-dimension ‘percentage of complete cells’, the best result is obtained by the AU portal, followed by the NZ and US portals which have approximately the same results. The worst result is obtained by the CA portal. As for the sub-dimension ‘percentage of complete rows’, the worst result is obtained by the CA portal. On the other hand, the best result is performed by the AU portal, followed by the US portal and then by the NZ portal. These results show that the retained portals published some datasets which have empty cells and consequently impact on the percentage of complete rows. Regarding the sub-dimension ‘eGMS compliance’, the CA portal performed the best for this sub-dimension followed by the AU and NZ portals. The US portal has the lowest result. The overall good results can be justified by the fact that most portals provide the required information (e.g. title, description, and publisher) for the metadata of their published datasets. Since our study focuses on CSV resources as we want to automate the calculation of data quality, we set the sub-dimension ‘five star open data’ to 0.6 (three stars) for all evaluated portals. For the sub-dimension ‘percentage of accurate cells’, the best result is obtained by the NZ portal, followed by the AU, CA, and US portals, which have approximately the same results. These excellent results show that most of the portals are filling the cells of their datasets with the appropriate datatypes.

In addition to these separate evaluations, we also average each sub-dimension across all portals to determine which sub-dimension performed best or worst. Based on [Figure 3](#) (see grey bars), we note that the sub-dimension ‘track of creation’ is the metric where most of the portals performed well, followed by the sub-dimensions ‘eGMS compliance’, ‘percentage of complete cells’, ‘percentage of accurate cells’, ‘five star open data’, ‘percentage of complete rows’ respectively. The worst result was performed by the sub-dimension ‘track of updates’.


**Figure 3.** Mean values by dimension for country portals.

## 4.2. Results by dimensions

Figure 4 presents the mean values by dimension for the selected country portals. In addition, we perform some statistical tests whose results are summarised in Table 4 to confirm whether one country portal performs better than another for each dimension. For the dimension ‘traceability’, all the portals have the same results since their results for the sub-dimensions ‘track of creation’ and ‘track of updates’ were also the same. As for the dimension ‘completeness’, the best result is performed by the AU portal followed by the US portal and the NZ portal respectively. The CA portal has the worst result for this dimension. For the dimension ‘compliance’, the worst result is obtained by the US portal. The best result is obtained by the CA portal followed by the AU and NZ portals which have the same results. These results show that most of the portals are trying to follow the standards in terms of data publication, especially in providing metadata information, but there is still room for improvement to achieve better results. For the dimension ‘accuracy’, most of the portals perform very well however the NZ portal performed better than the three other portals which have the same results.

Similar to the sub-dimension, we also average each dimension across all portals to determine which dimension performed best or worst. As shown in Figure 4 (see grey bars), the dimension ‘traceability’ has the lowest value, followed by the dimensions ‘completeness’ and ‘compliance’. The dimension ‘accuracy’ is the one for which most portals performed best.

## 4.3. Results by portals

Based on the results of the dimensions for each portal, we then average the values of the dimensions to calculate the data quality for each portal to determine which portal performs better. Referring to Figure 4 and Table 5, the AU portal has the highest data quality, followed by the NZ and US portals which have the same scores. The CA portal has the lowest data quality. These results can be justified

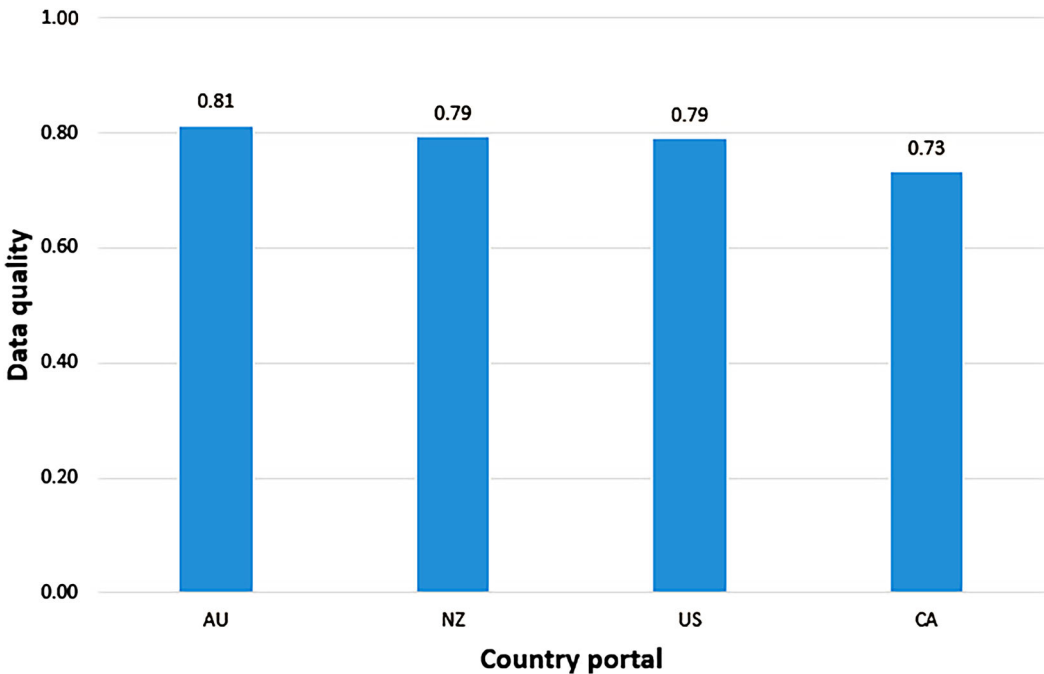


Figure 4. Data quality by country portal.

**Table 4.** Pairwise country portal comparisons by dimension.

Dimension	Pairwise country portal comparisons					
	AU-CA	AU-NZ	AU-US	CA-NZ	CA-US	NZ-US
Traceability						
Completeness	(AU > CA)*	(AU > NZ)*	(AU > US)*	(NZ > CA)*	(US > CA)*	(US > NZ)*
Compliance	(CA > AU)*		(AU > US)*	(CA > NZ)*	(CA > US)*	(NZ > US)*
Accuracy		(NZ > AU)*		(NZ > CA)*		(NZ > US)*

Only statistically significant comparisons are shown. Star represents significance level:  $*p \leq 0.05$

by the fact that with reference to the previous section, the AU portal performed best on most dimensions compared to the other country portals.

Furthermore, these results show that there are still some improvements to be done to portals to ensure their re-use. First, portals should provide details about their updates by implementing, for example, a versioning module in their portals. Second, portals should fill in all cells of their datasets to improve completeness, for example by using a simple Excel file to check for empty cells and fill them in before publication. Third, they should provide information about the metadata of their datasets and especially categorise each dataset to make it easier for reusers to search and navigate, because in the US portal (which has the lowest result on this dimension) the main issue was on this metric. Fourth, the portals should try to fill the cells of each column with the corresponding data-type and format to improve accuracy.

## 5. Discussion

Findings from the present study vis-a-vis the qualitatively advanced OGD portals of Australia are in line with the previous research which attests to the early adoption of OGD practices under the aegis of the leading ‘policy entrepreneurs’, i.e. the lead departments and agencies of the government (Chatfield and Reddick 2018). Even the usability assessment of the OGD portal of Australia among other countries showed Australia scoring the highest in terms of the three parameters, viz., data specification, feedback and requests (Machova, Hub, and Lnenicka 2018) – the research acknowledged the success of Australian OGD initiative in terms of the state-of-the-art data explorer and visualisation tools. Australian OGD portal is regularly updated and extensive (Power et al. 2015). Thus, Australia has succeeded to a great deal in making a transition from being secretive towards openness and transparency (Hardy and Maurushat 2017; Henninger 2018).

In the context of New Zealand, the relatively low performance of the OGD portal in terms of the quality given the variability of OGD file formats-as deduced in the present study-may be attributed to the fact that there are limited resources for cross-agency coordination and lack of interest in the government agencies to overly invest in ensuring the institutionalisation of the OGD initiatives (Oh 2013). The OGD portals of New Zealand are lacking in terms of data adequacy, accessibility, interoperability and infrastructure apart from inter-governmental coordination and user capabilities (Stats NZ 2021). Similar conclusions were also deduced in another study wherein the complexity and heterogeneity of OGD led to inefficacious OGD publishing procedures (Schindler, Dionisio, and Kingham 2018). Such bottlenecks dampen the OGDC processes, to admit the least.

In line with the findings from the present study, data quality of US portal is inadequate and this is owing to the inefficacious support from the key organisational personnel within and without

**Table 5.** Data quality pairwise country portal comparisons.

	Pairwise country portal comparisons					
	AU-CA	AU-NZ	AU-US	CA-NZ	CA-US	NZ-US
Data quality	(AU > CA)*	(AU > NZ)*	(AU > US)*	(NZ > CA)*	(US > CA)*	

Only statistically significant comparisons are shown. Star represents significance level:  $*p \leq 0.05$ .

(Krishnamurthy and Awazu 2016) and this serves as a major challenge in the development of OGDC. Conclusions similar to the present study were also found for the US OGD portals wherein it was shown that only whilst data-mostly incomplete – have been published via the portals, they are still ‘level one’ OGD, i.e. in PDFs and HTML formats and thus, they are not machine-processable (Yi 2019) – implying that the data quality is inappropriate (Dawes 2012). Complementing these findings with the previous research deductions that the OGD initiatives are ‘unevenly’ developed in the US (Nugroho et al. 2015), it is apparent that OGDC institutionalisation is far-fetched.

In the case of Canada, findings from the present study attest previous research findings that besides the fact that the Canadian national authorities are rampant upon furthering their OGD initiatives with relatively better quality, the municipal authorities are lagging behind and there is lack of coordination between the government agencies vis-a-vis data sharing (Roy 2014) and both of these facets are impediments towards an OGDC culture. Furthermore, the OGD initiatives are not being universally adopted by all the government agencies: case in point may be counted the Research Councils in the higher education sector which are not furthering OGD policies, let alone the publishing and dissemination dimensions (Lasthiotakis, Kretz, and Sa 2015). Likewise, in another case study, it was deduced how the Immigration, Citizenship and Refugees Canada (IRCC) did not engage completely in its OGD initiative’s refurbishment or furthered citizen engagement, for that matter (Gintova 2019). Such lacuna may be attributed to the lack of attention and policy directives from the end of the government agencies coupled with limited user engagement with the OGD platforms (Longo 2017). Concomitantly, other challenges linked with the OGD initiatives of Canada are associated with the changes in public policies, changes in the names of the administrative departments, the tendencies of removal or alteration of the content of the OGD portals (Paterson 2018) and even modulating the transparency commitments which is suggestive of the ‘closed’, unaccountable and insular tendencies of the government (Clarke, Lindquist, and Roy 2017). Thus, it is clear that steps need to be taken for OGDC to happen.

## 6. Conclusion

Two of the key challenges pertaining to OGD initiatives relate to digital asset management and archiving and preservation and both these dimensions are linked with KM practices. Taking cue from this, the present study sought to present a concept of OGDC besides providing an empirical grounding with four top-notch countries across OGD quality standards wherein it was deduced that quality of the datasets is important for the success of OGD initiatives and quality can be maintained only via robust KM practices among the administrative agencies. It needs to be appreciated that establishing a data governance infrastructure with facilitating foundations for knowledge sharing among the administrative agencies is not an easy task, however, short-term and long-term goals need to be chalked out for ensuring that sustainable and collaborative KM practices are being adopted by the government departments for furthering the cause of OGDC.

To appreciate the nuances of the research objectives, an empirical assessment was done of four of the top ten countries’ OGD portals in terms of their quality metrics given that quality is a factor of the KM practices being adopted by the government agencies. Findings from the study show that whilst Australia is in the forefront in terms of the quality parameters, and, hence, testifies its commitment towards developing an OGDC culture, other countries are laggards and steps need to be taken for quality improvisation through the interventions aimed at furthering inter-departmental coordination and support from the senior management executives. By proposing a concept of OGDC which rests its edifice on the inter-agency collaboration with a specific focus on the quality maintenance of OGD, the present study contributed to the twin-pronged challenges identified in the OGD initiatives’ efficacy, viz., implementation barriers and the barriers to use by the stakeholders. Furthermore, the study contributed to the knowledge corpus of OGD-KM dyad with its conceptual formulation, viz. OGDC, followed by the empirical validation.

Thus, the present study leaves some recommendations for the policy-makers, practitioners and society: first, a strategic vision needs to be chalked out by the governments horizontally and vertically with a point device aim of maintaining quality standards of the OGD portals via dialogue and discussion; second, and, in line with the first, a comprehensive plan document needs to be in place for chalking out the manner in which the OGDC culture may be imbibed by the governments; third, training and development needs of the concerned personnel as also the users should be met and this mandates a strong commitment towards OGD initiatives wherein budgetary allocations need to be made; and finally, myriad societal stakeholders' involvement is necessary for ensuring that the KM practices are furthered with the involvement of all those involved in data publishing and data consumption.

## 7. Further research pointers

With the conceptualisation of the OGDC, several indicators emerge that might be addressed in future academic pursuits. For one, it may be pertinent to understand how the commonality of OGDC across the administrative agencies of different countries might lend cues for the 'best practices' to be adhered to by all. Second, issues like governmental nature in terms of democracies and non-democracies as also the constitutional and statutory foundations might be of interest for those keen on unravelling the OGDC dimensions vis-a-vis legal informatics. Likewise, an understanding of the Knowledge Sharing Behaviours (KSBs) at the individual levels, i.e. the employee per se, might be of interest for the academicians interested in the behavioural public administration domains. Finally, though not conclusively, further research is merited to appreciate the relevance and implications of OGDC in the newer digital government formats like Gov 4.0 and beyond or the tension between Smart Cities vis-a-vis the conventional ones.

## Notes

1. Online supplementary material: [https://github.com/stutisaxenaogd/KM\\_Table-2](https://github.com/stutisaxenaogd/KM_Table-2)
2. <https://github.com/etalab/csv-detective>
3. <https://rb.gy/cdw5so>

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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