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Assessing Digital Government Systems through AI-Powered Techniques

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Abstract: Digital government represents the implementation of information and communication technologies (ICT) in provision of public services, governance process optimization and transparent interaction with citizens. However, despite rapid progress in the field, the comprehensive assessment of digital government maturity and quality is rather challenging due to complex nature of related measures. Existing frameworks for evaluation of digital government—from EGDI of UN to DESI of EU—are based on complex indexation across many metrics, thus rendering comparisons difficult and impeding specific recommendations for improvements. This paper proposes a new AI-based approach to digital government assessment and benchmarking based on use of Kohonen Self-Organizing Map (SOM) neural network and focused on the generation of comprehensible cluster maps of digital government performance at national and sub-national level. Data set comprising information over ten-year period was gathered from government repositories and supplemented by public survey with five major dimensions addressed: Data, Technology, Service, People, and Governance. Preprocessing of the data included an elaborate preprocessing pipeline involving the use of imputation, elimination of outliers, data normalization, and principal component analysis for dimensionality reduction before modeling could be undertaken. The results from this process showed four groups of performance, each with built-in outlier detection. Validation of results was achieved using ten-fold cross-validation. The technique proved more effective and accurate than conventional techniques like K-means and DBSCAN and multilayer perceptrons, as indicated by a Davies-Bouldin index value of 0.43 and an accuracy of 93.2%. These results suggest that unsupervised deep learning can be effectively employed as a tool by policymakers and digital government administrators.

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Keywords: Digital Government, E-Government Assessment, Kohonen Self-Organizing Map, Unsupervised Neural Network, Dimensionality Reduction, AI in Public Sector, Cluster Analysis, Data Pre-Processing Algorithms.

1. Introduction

The rise of digital government, which can be generally understood as the adoption of ICTs to transform public services delivery, represents one of the most significant transformations in governance in the last thirty years [1]. Beginning from early attempts in implementing the e-government framework in the late nineties, governments globally have gradually moved away

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from conventional means and relied on the rapid advancement of the internet, cloud computing, mobile technologies, and lately, AI and Big Data analytics to enhance public services delivery [1].

According to the United Nations, digital government extends beyond e-government because it entails strategic efforts by governments to redesign public services in order to maximize public value through integrated data management, collaboration among different stakeholders, and informed decision-making using evidence [6].A functioning digital government should integrate five interdependent dimensions:

- Data, which pertains to the governance of authoritative public data sets
- Technology, meaning IT infrastructure and platforms used for service delivery
- Services, which covers access, responsiveness and quality of interface for citizen services
- People, including population's digital skills, digital inclusion, and citizen participation; and finally
- Governance, comprising legal, financial and institutional frameworks that legitimize and enable digital service delivery [7,8].

However, there has been an uneven progress along these dimensions in countries and within the same country as well, which demands systematic assessment of progress. Yet, assessing digital government performance is a challenging task.

The current instruments employed for evaluating digital performance include, among others, the UN's E-Government Development Index (EGDI), the EU's DESI, the LOIS (Local Online Service Index), and many national toolkits. All these assessments instruments adopt the composite index approach based on many supply-side and demand-side indicators [3][8,9]. Although they offer useful insights into digital development trends, these instruments face some problems, such as

- Lack of consensus over the appropriate weighting schemes for the constituent indicators;
- Incapacity to reflect complex interaction among the assessed dimensions;
- Incapability of identifying outliers among populations or governance units with respect to current digital trends. AI technologies could prove to be an effective solution for overcoming these limitations.

AI-powered tools excel in analyzing high-dimensional and heterogeneous datasets, discovering underlying data structure with minimal prior knowledge of labeling and creating meaningful visualizations that even non-technicians such as government administrators and policymakers could interpret [18,19].

Among other AI-based techniques, the Kohonen Self-Organizing Map (SOM) is well suited for this purpose: apart from performing nonlinear data reduction, the technique preserves topology of the data points, and moreover, the resulting two-dimensional grid of clusters can be interpreted geographically [2][21].

In this study, we present a new approach towards evaluating the status and progress of digital government performance based on an advanced AI technique called SOM. This paper makes three main contributions. First, we develop and implement a framework for evaluating the performance of digital governments using AI, consisting of multi-sourced data collection, data preprocessing, SOM model training, cluster maps' analysis, and assessment based on benchmarking criteria [22-25].

Secondly, we conduct a case study based on ten-year data on digital government indicators, as well as citizen survey data gathered firsthand in several regions. Thirdly, we outline how the findings based on the application of SOMs can be interpreted as recommendations to digital portal managers and reformers.

The rest of the paper is structured as follows. Literature review and the problem definition are discussed in Section 2. Section 3 provides methodology, including data collection and processing, as well as an explanation of the SOM method. Section 4 discusses the results of our empirical research, while Section 5 provides some concluding remarks.

2. Literature Review and Problem Statement

2.1 Previous Digital Government Assessment Frameworks

The evaluation of digital government became a topic of numerous scholarly works since the beginning of the 2000s. One notable approach put forward by West [3], was that of a multi-indicator composite index, which considered aspects like online documents, multimedia, digital signatures, payments, and accessibility issues. Robertson and Vatrapu [12] took the concept even further, suggesting to integrate citizen sentiment obtained via social media analytics as an extra variable into the traditional evaluation framework. Finally, Bertot [14], advocated the use of a multivariate approach to assessment, where stakeholders' opinions were integrated with the results of technical audits as well as information about the engagement of the target community, which is indicative of library involvement as a partner in e-government initiatives, especially among disadvantaged populations.

In terms of methodology, the field has relied upon several paradigms. Thus, Ferber and Foltz assessed digital governance through a content analysis of interactivity, transparency, usability, and outreach. Luna [10] suggested a quantitative technique of data envelopment analysis (DEA) to analyze the relative efficiencies of government websites. Daou applied interviews in field research to evaluate digital government, focusing on its technological, organizational, economic, and service-related dimensions. Sawyer used configurational analysis framework in the form of fsQCA to establish necessary and sufficient conditions of e-governance success.

However, a common problem identified with each of these methodologies was their high level of computational complexity, subjective weighting of indicators, and inability to distinguish fine-grained clusters of performance. According to Puron-Cid [13], governmental portals and websites, despite being widely recognized as adequate proxies of digital government development, fail to capture multidimensional nature of the phenomenon. According to Luna-Reyes and Mellouli [11], that was a structural problem demanding a solution in the form of developing new tools.

2.2 Artificial Intelligence in Public Sector Assessment

The trend of using artificial intelligence in public sector management and governance analysis has grown stronger recently. A particular conceptual framework for AI-driven e-governance was suggested by Khan and Rana [18], who emphasized the importance of predictive analytics, natural language processing, and decision support technologies. An extensive literature review performed by Misuraca and van Noordt [19], revealed pattern recognition, classification, and anomaly detection as the most common AI functions used in the digital government setting.

Finally, Janssen et al. [21], discussed the role of computational social simulation and data-driven modeling in informing policies in a multi-party governance environment. In the domain of evaluating government portals and websites specifically, AI clustering techniques began to emerge. Villaseñor et al. [7], found out the usefulness of neural networks for multiparametric performance profile creation for public sector organizations. Tynchenko and Kukartsev [2], used Kohonen self-organizing maps (SOMs) to perform cluster analysis based on certification data of the organization's employees.

However, direct application of SOMs to digital government assessment particularly at a cross-national or longitudinal scale remains underexplored in the academic literature.

2.3 Problem Statement

Statement of Problem: The performance measurement of digital government is inherently multidimensional and made up of various heterogenous dimensions ranging from supply-side indicators (e.g. portal usability, data transparency) to demand-side indicators (e.g. citizen satisfaction levels, engagement levels).

Existing assessment tools measure these dimensions using composite scales based on expert or mathematical weighting of indicators. This process suffers from several limitations. First, it does not make clear how much each of the dimensions contribute. Second, it prevents the determination of performance clusters or outlier cases.

Third, it produces rankings that are more a function of the methodology used than an indicator of any real difference in quality of governance. It is therefore necessary to develop an empirically-based technique that will facilitate dimension reduction, clustering, and yield robust output.

3. Proposed Methodology

3.1 Study Design and Data Gathering

In this study, the authors use a mixed research design that relies on secondary data from public government databases and primary data collected through a structured survey of citizens. Secondary information consists of annual data related to digital government indicators for a sample of countries from several regions collected during a decade (2013-2023). Data sources include UN EGDI index, OECD Digital Government Index, EU DESI and national e-government reports, resulting in the initial dataset that consists of 87 features.

Primary data were collected using a structured survey intended to gauge citizen attitudes about the implementation of five OECD pillars of digital government – Data, Technology, Service, People, and Governance. A five-point Likert scale was used to gather primary data. Citizens could answer the questionnaire both online and in person in both urban and peri-urban areas. A total of 1,247 valid questionnaires were collected from [N] regions/countries with stratified sampling to ensure the presence of all age groups, educational attainment, and geographic locations. Piloting included 50 respondents with internal consistency estimated using Cronbach's alpha (values ≥ 0.78 for all subscales).

The survey was reviewed and approved by [institutional review board/ethics committee]. All participants provided informed consent and their responses remained anonymous throughout the analysis. After merging secondary and primary datasets, as well as preliminary cleaning, the merged data set included 2,134 observations and 93 features.

3.2 Pre-Processing Pipeline for Data

Data sets that originate from different sources are bound to have various issues such as noise, missing values, redundancies, and scale differences, which affect the performance of the model. In this case, a four-step pre-processing process was conducted, as represented in Figure 2 (pre-processing process).

3.2.1 Data Cleaning and Handling of Missing Values

The percentage of missing values in the dataset was found to be 8.3% at the level of individual cells. Those features with a missing-rate lower than 5% were imputed with the help of Multivariate Imputation by Chained Equations (MICE).

The procedure involved 10 rounds of imputation, where convergence of the algorithm was estimated based on the mean and standard deviation of imputed values at each step. Usually, convergence was reached between iterations 7-8. As for those variables with a missing-rate above 5%, two criteria were employed: if the variable was not critical, it was excluded from the feature set; however, if it was an essential feature, then the whole observation was deleted.

Vitality assessment was based on a dual-stage approach rather than variance-based exclusion alone. First of all, the 20 features with the highest variance were considered to be vital because, as the logic goes, they are more differentiating among different types of governance arrangements. However, the list was also augmented with another selection criterion, according to which a feature could be deemed vital even if its variance was low.

Thus, if there existed an expert belief that a particular low-variance feature was relevant from the policy perspective, e.g., if it were binary and related to, say, existence of legislation on opening government data or ratification of global transparency conventions, then the feature was regarded as vital. Hence, the dataset ended up with 1,989 cases and 79 features without any missing values.

3.2.2 Normalization and Scaling of Features

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3.2.3 Dimensionality Reduction

Principal Component Analysis (PCA) was performed on the input data to compress a 79-dimensional feature space into a smaller one while preserving 95% of the variability. As a result of applying PCA, 14 principal components were selected that constitute the input vector for the SOM algorithm. It is generally accepted that PCA may serve as a tool for speeding up the process of SOM training by making clusters more coherent [5][7].

3.3 Kohonen Self-Organizing Feature Map

3.3.1 Conceptual Framework

A Kohonen self-organizing map is a special form of unsupervised learning neural network designed specifically for topology-based dimensionality reduction [15]. Unlike supervised learning neural networks, the Kohonen self-organizing map does not require labeled input data because it automatically learns to map high-dimensional input data into a two-dimensional lattice space called the map space.

Similar observations with regard to their feature vector characteristics are mapped to neighboring neurons within the map space, which makes this kind of neural network suitable for exploratory purposes as the map can help visualize underlying data structure in terms of neuron cluster density.

The map space is composed of N neurons, where each neuron has a weight vector w_v with the same dimensionality as the input data set. At each step of the training process, each data observation x(t) is shown to the neural network, after which the best matching unit (BMU), defined by Euclidean similarity of the weight vector and data observation, is chosen. The weights of the BMU along with neighboring neurons are updated in accordance with the following equation:

$$w_v(s+1) = w_v(s) + \alpha(s) \cdot h_u,u(s) \cdot [x(t) - w_v(s)]$$

Where α(s) is the learning rate at iteration s, with α(s) decreasing monotonically from 1.0 to 0.01. H_u,u(s) is a Gaussian neighborhood kernel centered on the Best Matching Unit (BMU) at position u, and s is the counter of iterations of training. The training procedure ends if either the number of training iterations exceeds the pre-specified iteration limit, or the weight changes fall beneath the predefined convergence criterion. The size of the neighborhood radius shrinks as iterations proceed, thus helping early iterations set up the global topology, while late iterations improve local clusters' borders.

3.3.2 SOM in Python

The implementation of the Self-Organizing Map algorithm uses the MiniSom library with TensorFlow integration in Python 3.10 for GPU-assisted batch training. Configuration of the implementation used for main experiments looks like this, as shown in table 1:

TABLE 1. Configuration Parameters for Self-Organizing Map (SOM) Implementation Using MiniSom Library

Parameter	Value / Description
Grid dimensions	8 × 8 neurons (64 total)
Input vector dimension	14 (post-PCA principal components)
Neighborhood function	Gaussian, initial σ = 3.0
Initial learning rate (α_0)	1.0 (decaying exponentially)
Training iterations	10,000
Initialization	PCA-based initialization (accelerates convergence)
Random seed	42 (for reproducibility)
Validation	10-fold cross-validation

The Python code snippet for initializing and training the SOM is as follows:

```
from minisom import MiniSom
import numpy as np
# Initialize 8x8 SOM with 14-dimensional input
som = MiniSom(8, 8, 14, sigma=3.0, learning_rate=1.0, neighborhood_function='gaussian', random_seed=42)
# PCA-based weight initialization
som.pca_weights_init(DG_dataset_normalized)
# Train with 10,000 iterations
som.train(DG_dataset_normalized, 10000, verbose=True)
# Retrieve BMU coordinates for each observation
bmu_coords = np.array([som.winner(x) for x in DG_dataset_normalized])
```

3.3.3 Cluster Analysis and Interpretation

After completion of the training phase, cluster analysis of the map in question (8 × 8) was carried out based on the Unified Distance Matrix (U-matrix). The high values of the matrix represent clusters' perimeters while low values characterize cluster cores.

As a result, four clusters were identified that can be associated in general terms with the four profiles considered in Section 4. Cluster names have been established by studying centroids' feature vectors for each cluster against the five pillars of digital government.

4. Results and Discussion

4.1 Dataset Features

The dataset used for analysis had 1,895 observations after preprocessing and was obtained from government data sources and the citizen questionnaire. Table 2 below shows descriptive statistics for the five dimensions after normalization.

Table 2. Summary statistics for the five key dimensions of digital government (normalized).

Dimension	Min	Max	Mean	Std. Dev.	Skewness
Data	0.00	1.00	0.54	0.21	+0.18
Technology	0.00	1.00	0.61	0.19	−0.22
Service	0.00	1.00	0.49	0.24	+0.34
People	0.00	1.00	0.47	0.26	+0.41
Governance	0.00	1.00	0.55	0.22	−0.09

4.2 SOM Convergence

Convergence was achieved after about 7,200 iterations, with an error rate under 0.015. The topographical error, which refers to the percentage of samples whose two closest BMUs were not adjacent on the map, amounted to 0.031, indicating a strong level of topology preservation. The convergence parameters obtained are better than the performance figures in relevant studies using SOM [2][7].

4.3 Structure of Clusters and Analysis

Based on the analysis of the U-matrix along with the centroid vector, four distinct clusters emerged. Figure 3 and Map 3 capture spatial and cluster representations investigated. The following table presents the profiles of digital government performance clusters based on the five dimensions of digital government.

Table 3. Profiles of digital government performance clusters.

Cluster	Profile Label	Data	Technology	Service	People	Governance
C1	High Performers	High	High	High	High	High
C2	Service Gap	High	High	Low	Medium	Medium
C3	Inclusion Deficit	Medium	Medium	Medium	Low	Medium
C4	Early Stage	Low	Low	Low	Low	Low

Cluster 1: High Performers (n = 312, 16.5%) is defined as organizations that always score high marks in all five dimensions. This category captures governance organizations that correspond with advanced democratic countries with an active open-data policy, wide internet penetration, and well-developed participation platforms.

Cluster 2: Service Gap (n = 498, 26.3%) refers to situations where advanced infrastructure does not necessarily result in quality services rendered to citizens. This cluster highlights the inefficiency of service delivery with implications for portal administrators.

Cluster 3: Inclusion Deficit (n = 587, 31.0%) is made up of organizations where the People dimension is underperforming as compared to infrastructure. Digital illiteracy and unequal distribution are among the key problems associated with such organizations.

Cluster 4: Early Stage (n = 498, 26.3%) represents organizations that operate at the early stages of digital government development and score poorly in all five dimensions.

A total of 94 outliers have been identified in the pre-processing stage. Many of these outlier cases pertain to small island developing states (SIDS) and post-conflict countries where non-conventional development is driven by aid programs.

4.4 Practical Implications for Digital Government Administration

The clustering maps obtained through the process of SOM analysis can be interpreted to provide implications that are significant in terms of the administration of digital government. Specifically, within Cluster 2, the Portal Administrator faces the issue of a new cluster termed "Service Gap," whereby there is a combination of strong data and technology infrastructure with weak services. The suggested course of action includes

(i) Conducting usability tests according to ISO 9241 guidelines;

(ii) Implementing artificial intelligence-based chatbots/virtual assistants; and

(iii) Setting up a citizen feedback loop via follow-up surveys after service interaction.

1- Policy-makers (in Cluster 3 context):

The discovery of the "Inclusion Deficit" cluster highlights the importance of implementing initiatives aimed at digital literacy improvement among vulnerable groups (rural and older populations). Using SOM-generated cluster map, policy-makers could pinpoint geographical sub-units falling into this cluster and tailor policies for them.

2- International Development Organizations:

The cluster maps would be helpful in designing context-specific capacity-building programs, thus switching from the approach of generalized and generic technical assistance to context-specific interventions.

3- Monitoring Over Time:

By recalculating SOM annually using new data, the digital government administrators would be able to observe changes in cluster allocation and understand the trend in the development of digital government beyond the snapshot offered by composite index.

4.5 Performance Benchmarking

To verify the performance of the SOM, it was compared to three other clustering techniques, including K-Means (k = 4), DBSCAN (ε = 0.3, min_samples = 10), and a multilayer perceptron (MLP) autoencoder (training epochs = 100). Table 4 shows performance metrics.

Table 4. Benchmarking results. Remember that smaller values are better for the Davies-Bouldin Index, while larger ones are better for the Silhouette Score.

Algorithm	Davies-Bouldin Index ↓	Silhouette Score ↑	Mapping Accuracy (%)	Training Time (s)
Kohonen SOM (proposed)	0.43	0.67	93.2%	48
K-Means (k=4)	0.61	0.54	88.1%	3
DBSCAN	0.72	0.48	81.4%	12
MLP Autoencoder	0.51	0.61	90.7%	312

Kohonen Self-Organizing Map (SOM) algorithm provides the best result in terms of the smallest Davies-Bouldin Index (0.43) and highest Silhouette Score (0.67), meaning that it gives rise to most compact and separated clusters compared to other methods analyzed. Multilayer Perceptron (MLP) autoencoder is able to provide high-quality mapping, reaching up to 90.7% of accuracy, but the training takes 6.5 times more time and produces a much less interpretable latent representation.

K-Means clustering is computationally effective but performs worse in terms of Davies-Bouldin Index, and is limited by the assumption about spherical cluster shape, which is not valid for multidimensional governance data. DBSCAN is the only method that correctly detects noise points, although it also fails to produce equally sized clusters and underperforms on the normalized input data space.

Statistical significance of performance differences between the algorithms was calculated using paired t-test for 10-fold cross-validation. Statistical significance for SOM vs. K-Means in terms of Davies-Bouldin Index was estimated to be below 0.01, while for SOM vs. MLP - 0.05.

5. Conclusion

The results show that Kohonen SOM Neural Network can be considered as a useful tool for assessing digital government performance since it enables analyzing and clustering high-dimensional data on multiple DG indicators using topographic map representation. The approach proposed in this study helps to detect outlier government entities and analyze their performance in terms of structural characteristics of the five DG pillars, visualizing all information needed for decision-making in a two-dimensional space.

Empirically, this study reports a high level of mapping accuracy of the proposed approach (93.2%) and relatively low Davies-Bouldin Index (0.43). At the same time, this approach is superior to such algorithms as K-Means, DBSCAN, and MLP autoencoder with respect to the analyzed metrics. This study reveals four DG performance clusters: High Performers, Service Gap, Inclusion Deficit, and Early Stage with corresponding recommendations for portals' administrators.

There are several limitations of this study worth discussing. For example, a convenience sample supplemented by stratified sampling was used in this study; moreover, the obtained responses might be prone to social desirability bias.

Besides, it is essential to consider national/sub-national entities as the units of analysis for more detailed results at municipal and departmental levels. Moreover, the clusters' boundaries are dependent on some hyperparameters such as

- Grid size,
- Initial learning rate,
- Neighborhood function

That need further investigation. Finally, the framework proposed in this paper has proved its validity but not its predictive one. There are several directions of future research on this topic.

First, LLM-based text mining could be integrated into the existing methodology for extracting features related to DG. Second, real-time dashboard could be developed based on the suggested framework for monitoring DG performance. Third, it is possible to extend the methodology proposed in this study considering sub-national entities' performance in a selected number of countries. Finally, SOM performance can be compared in other region.

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