Exploring e-maturity in Italian Local Governments: Empirical Results from a Three-step Latent Class Analysis

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Points for practitioners

- When assessing e-maturity, municipalities should treat differently Government to Citizen and Government to Business services
- Currently, municipalities are focused more on the digitization of Government to Business services
- Socio-economic and environmental factors have a partial effect on e-maturity. The size of the municipality and the income per capita are the most significant indicators
- E-maturity raises effectiveness without a clear effect on efficiency. Only when reaching a fully accomplished e-maturity a slight effect on municipalities' expenditures can be detected

Abstract

This article undertakes a quantitative and holistic approach to frame a model of e-maturity in local governments, defined as the extent to which technologies permeate public service delivery. Moreover, the study adds evidence on the performance associated with different levels of e-maturity. In so doing, we collect survey data from 814 Italian local governments and integrate it with secondary sources. We propose a new angle for assessing e-maturity at local government level, where the novel approach is the categorisation of public services on the basis of their final users. The application of a Latent Class Analysis (LCA) shows that the level of e-maturity is quite limited among Italian local governments and that most of them tend to prioritise *government-to-business* rather than *government-to-citizen* services in their digitisation process. A high level of e-maturity is associated with greater effectiveness rather than efficiency.

Keywords: e-government; e-maturity; service delivery; local government; performance; empirical study

1 Introduction

Since the early appearance of information and communication technology (ICT), public sector scholars started looking for a proper way to assess digital maturity (hereafter e-maturity), which has been defined as the extent to which a public organisation is using digital technologies for managing and delivering public services (Layne and Lee, 2001). Despite the increasing body of academic research on models for assessing e-maturity and identifying its driving factors, there is no clear pattern emerging from literature (Andersen et al., 2020).

Moreover, scholars started questioning the impact of ICT on organisational performance, in terms of both efficiency and effectiveness (Budding et al., 2018; Nam, 2019). Efficiency is defined as the ability to minimise inputs while maximising outputs, whereas effectiveness deals with the quality of service deployed.

So far, two main challenges have impeded scholars in reaching consensus on the aforementioned topics: (i) identifying a way to assess e-maturity on a large scale (Coursey and Norris, 2008; Scholta et al., 2019) and (ii) identifying proper performances indicators, especially when looking at efficiency (Budding et al., 2018).

This article adds evidence that enriches the current body of knowledge on both issues. First, it offers a new lens for looking at e-maturity that takes into consideration the end-user of a public service (Yildiz, 2007) and explores the environmental and socio-economic factors predicting e-maturity. Second, it investigates the relationship between e-maturity and different sets of indicators.

In so doing, we rely on a survey distributed to all Italian local governments (hereinafter also ‘municipalities’), collecting 814 responses (around 10% of the Italian local governments). We propose a measurement model based on a Latent Class Analysis (LCA) through which we contribute to filling a gap in quantitative studies on ICT in the public sector (Wirtz and Daiser, 2018). Finally, we test the presence of a relationship between e-maturity, socio-economic factors, environmental factors, efficiency, and perceived effectiveness.

The remainder of this paper is organised as follows. Section §2 reviews the literature in the field. Section §3 describes the available data. Section §4 illustrates the methodology and the conceptual framework. Section §5 contains the results, which are discussed in Section §6. Section §7 defines lines for future research and concludes.

2 Literature review

The literature on e-maturity is embedded into the broader discussion on ICT in the public sector, mostly referred to as ‘e-government’. This term, broadly defined, refers to the use of ICT for better public service delivery (Yildiz, 2007) and has stimulated scholars to define and assess the level of digital maturity, thus fostering e-maturity models (Andersen et al., 2020). Three research areas are particularly relevant: (i) the definition of e-maturity, (ii) the determinants of e-maturity, and (iii) the association of e-maturity with effectiveness and efficiency.

Defining e-maturity

E-government scholars propose several models for characterising e-maturity (Coursey and Norris, 2008; Layne and Lee, 2001; Lee, 2010; Scholta et al., 2019). As a guiding principle, scholars divide e-maturity into a series of sub-sequential steps (Coursey and Norris, 2008). The first model that inspired the research in this field was presented by Layne and Lee (2001), who developed a four-stage model based on technical, organisational, and managerial feasibilities (1. Catalogue, 2. Transaction, 3. Vertical integration, 4. Horizontal integration). This latter model, like the majority of the e-maturity models, is based on theoretical reflections and looks at the possible future developments offered by ICT (Scholta et al., 2019; Layne and Lee, 2001). By design, those frameworks are not applicable for assessing e-maturity on a large scale, as the empirical base relies on extremely innovative public organisations that would emerge as positive outliers in a distribution (Andersen et al., 2020).

Only a minority of the e-maturity frameworks were designed with explanatory purposes, i.e. for assessing e-maturity on a large scale (Andersen et al., 2020; Budding et al., 2018), leaving space for further research in the field (Budding et al., 2018). Among these models, West (2004) identifies a set of items for assessing e-maturity through the screening of governmental websites. The data collected was also used by Das et al. (2017) in their longitudinal study, while Budding et al. (2018) based their research on survey assessment. The three aforementioned examples follow a similar path for assessing e-maturity, as they refer to a 4-point scale like the one proposed by Layne and Lee (2001).

Results from these studies show the possibility for e-maturity models to be (i) detectable on a large scale and (ii) simple in their research design (Budding et al., 2018; Das et al., 2017). However, they are also based on three assumptions that were recently criticised: (i) the need of achieving an end-state (ii) the implicit assumption of linearity (i.e. an obligatory path to follow), and (iii) the independence from the external context (Andersen et al., 2020; Janowski, 2015). In detail, the dynamics that characterise and explain e-maturity are extremely diverse, thus it is not possible to identify and suggest neither an ‘optimal’ e-maturity level valid for all public organisations, nor a predefined path or clear subsequent steps to follow for moving towards digitisation (Andersen et al., 2020). On the opposite, e-maturity is extremely dependent from several characteristics of the context a public organisation is embedded in (Budding et al., 2018). Above all, the characteristics of the end-users (i.e., citizens, firms, associations, etc., hereinafter also referred synthetically as ‘users’) have proved to be relevant: the complexity of a service strongly depends on users’ needs (Tangi et al., 2021), which in turn affects the organisational dynamics within the division in charge (Weerakkody et al., 2019).

In light of these premises, our focus is not on the path to e-maturity but on its definition on the basis of the users and this represents a novel way to categorise services. The three main user-centred categories, widely accepted among scholars, are Government to Citizens (G2C), Government to Business (G2B), and Government to Government (G2G) (Yildiz, 2007).

E-maturity determinants

Previous research identified a set of factors that influence e-maturity, which included the internal organisational characteristics (organisational factors) and the external context, both in terms of socio-economic and environmental factors. These factors can be described as follows:

- Organisational factors. ICT introduction often gets stuck on embedded norms, processes, and structure that hinder innovation (Cinite et al., 2009). Moreover, the organisational culture and attitude towards innovation play a dominant role in influencing e-maturity (Nasi et al., 2011), as well as political and managerial motivation (Tan et al., 2020).

- Socio-economic factors. The socio-economic context surrounding a public organisation proved to have an influence on e-maturity. In detail, the income per-capita is extensively used as a proxy for the socio-economic level and was found to be positively associated with e-maturity (Budding et al., 2018; Manoharan, 2013).
- Environmental factors. Previous studies identified population, population density, and age as predictors of e-maturity, (Budding et al., 2018; Jacob et al., 2019). Moreover, the geographical location has often been associated with heterogeneous levels of e-maturity for cultural differences (Nasi et al., 2011) or different access to IT-infrastructure (Jacob et al., 2019). In this respect, evidence related to the Italian context, in which the morphology of the territory makes the presence of mountain municipality particularly relevant, show that this cluster of municipalities tends to have a poorer ICT infrastructure and a lower extent of ICT training (ISTAT, 2010). This fact makes the relation between e-maturity and geographical factors worth to be further investigated. Finally, collaboration forms and shared service were considered as a driver for technological development (Boudreau and Bernier, 2017).

Manoharan (2013), based on a combination of surveys and website content analysis and through a regression analysis, assesses the progress of e-maturity across counties in the United States. The author demonstrates that socio-economic and environmental factors influence e-maturity. Budding, Faber, and Gradus (2018), using survey data for Dutch local governments and regression analysis, demonstrate that environmental factors, and in particular population, population density, percentage of elderly (65 years and older), and young population (younger than 20 years) are key predictors of e-maturity. In contrast, the income level and the average level of education do not significantly influence e-maturity.

Nasi, Frosini, and Cristofoli (2011) collect a survey from Italian local governments, and, looking at the descriptive statistics, find that organisational factors play a prominent role in e-maturity, while socio-economic and environmental factors are less relevant – which differs from Manoharan (2013) and Budding et al. (2018). Our analysis adds evidence on an issue still debated, employing data from a novel survey that covers a large number of municipalities in Italy.

E-government: effectiveness and efficiency

A limited number of studies quantitatively assess the relationship between government efficiency and/or effectiveness and e-maturity, and the majority of them focus on transparency and accountability (Bertot et al., 2012; Lourenço, 2015). Among the studies that consider both efficiency and effectiveness, Nam (2019) selects various global indicators to state that, at a national level, e-maturity contributes to government effectiveness but does not improve efficiency. The main limitation is that all the indicators are based on expert perceptions. On a similar strand, Manoharan (2013) claims the presence of a relationship between e-maturity, efficiency, and effectiveness at the local level. However, as for Nam (2019), the author uses survey data, thus limiting the results to the managerial perception. Similarly to our study, Budding, Faber, and Gradus (2018) combine survey data and financial indicators and claim that there is not enough evidence to state a relationship between efficiency and e-maturity.

Existing studies highlight that the topic is still debated (Budding et al., 2018). The difficulties in collecting valuable and robust data on efficiency and effectiveness measures bring to several limitations in data collection (for example, by favouring self-declared data) and in data analysis (for example, by limiting the analysis to descriptive statistics).

We contribute to this stream of literature by providing additional evidence about the relationship between e-maturity and performance. Moreover, we do not limit our analysis to perception data but we include novel efficiency indicators that consider local governments' expenditures. Although our data do not allow causal inference, the statistical tools employed in this work point at identifying robust associations that can drive reflections about policy and managerial consequences of e-maturity and the performance of the local governments.

3 Methods

Research design and data collection

The empirical strategy for the study focuses on two different data sources:

- Survey data. A survey was designed and delivered to all Italian local governments, aiming at (i) assessing e-maturity and (ii) collecting the perception of the respondents on the impact of e-maturity in terms of effectiveness. This dataset is novel, and a specific heritage of the study. This is the typical database that is missing in the administrative records, and that can complement knowledge of the e-maturity phenomenon and its performance.

- Secondary sources. Other data were collected from different sources, with reference to (i) socio-economic and environmental factors and (ii) financial indicators. Organisational factors were not taken into consideration due to the absence of secondary data on a large scale in the Italian context.

Before going into further details, it is worth providing some background information on the empirical context. Italian public administration is characterised by a large number of local governments (7.904) and consequently a high level of fragmentation in governmental activities. The majority are small organisations (around 80% of the Italian local governments have less than 5.000 inhabitants). Local governments are characterised by a high degree of autonomy in determining the best way for delivering public services, in accordance with the characteristics of the administrated territory and the political and managerial inclination to innovate. This context has brought about much potential heterogeneity in e-maturity.

Survey

The survey was addressed to the IT manager of each municipality (in Italy every public organisation must identify an IT manager by law). To allow cross-checking of the survey data with secondary sources of information, the identification code of the local government was asked for at the beginning of the survey.

Before sending out the survey, a first round of interviews with four public managers was conducted to verify the intelligibility and the completeness of the questionnaire. After that, the questionnaire was revised, and a second pilot test was run. The survey was sent out in January

2019 to all Italian local governments via their official public e-mail address. Three rounds of recall were run in March, April, and June 2019. The survey was finally closed at the end of September 2019. Overall, a sample of 814 municipalities (around 10% of the Italian local governments) filled out the survey and this makes up the sample for our analysis.

To assess the level of e-maturity, we limited the concepts of e-maturity to the digitisation of the front-end, i.e. the portion of the service tangible by the user. This choice is also coherent with previous studies (e.g. Budding, Faber, and Gradus (2018)), allowing the comparison of our results.

For the purpose of our study, a sample of 10 public services was identified (Table 1, see online). The services were selected according to the list of local public services published on the Italian national Open Data portal. The following inclusion criteria were adopted:

(1) Variety of the divisions providing the service, to have a picture that is a good proxy of e-maturity in the entire organisation, in coherence with our unit of analysis – the local government.

(2) Inclusion of Government to Citizens (G2C) and Government to Business (G2B) services seeking equality in the number of G2C and G2B services, in line with our idea of including this distinction when looking at e-maturity.

(3) Inclusion of only services provided by all the Italian local governments.

G2G services were excluded from the analysis because delivering G2G is not the primary scope of local governments and because of the absence of a comprehensive list.

For each service, the level of e-maturity was assessed based on the following scale, originating from the one proposed by Budding et al., (2018):

(1) Non-Digital - the users (citizens or businesses) must go to the counter to access the service.

(2) Online Form Availability – Possibility to download the form from the institutional website but need to deliver it manually.

(3) Partially Online Service Availability - Opportunity to access the service online but only for a portion of it.

(4) Fully online Service Availability – Possibility of accessing the service online.

In addition, we measure the perceived benefits coming from digitisation using a five-point Likert scale question. The aspects assessed concern (i) the level of transparency; (ii) the number of communication channels open to citizens and firms and (iii) the quality of the services provided.

Other sources of data

Other data sources were integrated to identify the factors that influence e-maturity, and the financial indicators that can be affected by it. Table 2 (see online)lists the socio-economic and environmental factors taken into consideration for the analysis; the selection was driven by previous literature, as indicated in the last column, and data availability (for example, we had to exclude the education level (Budding et al., 2018)). The main source of information was the national statistical agency database (ISTAT).

Table 3 (see online) lists the efficiency and effectiveness indicators. For efficiency, indicators were extracted from AidaPA, a database that collects financial data yearly on local public authorities in Italy. To the best of our knowledge, the current study is one of the first examples to exploit the potential of these indicators, integrating them with other data sources. For the set of financial indicators, extracted with reference to the year 2018, we consider both the absolute value and the deviation from the average of the local governments of a similar size, with the aim of avoiding results driven by endogenous heterogeneity (in this case, driven by the local governments' size):

$$Dev\ Ind_x = \frac{Ind_x - \frac{\sum_{i=1}^{n} Ind_i}{n}}{\frac{\sum_{i=1}^{n} Ind_i}{n}}$$

$$x = 1 \dots n \rightarrow municipalities\ in\ the\ same\ category$$

In terms of effectiveness, the indicators originate from previous studies. While transparency has already been investigated at a local level by Manoharan (2013), higher service quality and better communication with citizens derive from the analysis done by Nam (2019) at a national level.

Statistical model

The methodology used is a 3-step Latent Class Analysis (LCA), a mixture modelling technique increasingly used to identify latent subgroups within a population (Muthén and Muthén, 2000). By latent subgroups, we mean clusters of observations (in this case, local governments), which share underlying common features in terms of important dimensions – specifically, those that are at the heart of conceptual interest (in our case, the level of e-maturity). Nonetheless, the way the observations can be grouped cannot be observed directly, and so the "latent" relationship is modelled using appropriate statistical techniques.

The 3-step procedure suits the purpose of this study well. In Step 1, the latent classes are defined based on 10 indicators (one for each of the services listed in Table 1) of the level of e-maturity of the local governments' services. All the indicators have been dichotomised, meaning that a value equal to 1 represents a service that has been digitised (equal to a value of 3 or 4 in the original scale), while a value equal to 0 means that the service has not been digitised (corresponding to a value of 1 or 2 in the original scale). We combine values 1 and 2 because they refer to a delivery mode in which the user still needs to go to the counter, thus, *de facto*, it is similar to a traditional service. As a result of the first step, each observation (i.e. each local government) is assigned to the group for which the probability of class membership is the highest. In Step 2, multinomial regressions are run in order to characterise the groups by means of the socio-economic and environmental factors described in the Section about the *Other sources of data*. Finally, Step 3 makes it possible to verify whether the distal outcomes vary across groups, to test whether groups with different levels of service digitisation report differences in their financial indicators or in perceived level transparency, quality of service, and communication. The measurement model is summarised in Figure 1 (see online).

The model was run using Mplus version 7.4, and we followed the literature on the topic to determine the number of latent groups (Nylund et al., 2007). In this procedure, the number of classes was selected assessing the goodness of fit of the model through the Bayesian Information

Criterion (BIC) and the Lo-Mendell-Rubin (LMR) test (Lo et al., 2001). In detail, the procedure consists of adding classes stepwise to the model testing its goodness of fit. Indeed, when the BIC indicates a minimum value for the K-class model, that K number of classes should be retained. The LMR test also compares the K-1 model with the K-class model. When the p-value of the LMR test is not significant anymore, then the K-1 class model should be selected. Moreover, we use entropy as an indicator of good separation between classes. The closer the entropy is to 1, the better the model's specification (Celeux and Soromenho, 1996).

In Step 2, class assignment is regressed against a set of socio-economic and environmental covariates to provide a useful characterisation of the latent groups. In this multinomial logistic regression, the largest class is used as the reference group, according to which odds ratios are provided to estimate the likelihood that a certain characteristic recurs in relation to the reference group.

Finally, Step 3 was modelled using the BCH procedure as suggested in literature (Asparouhov and Muthén, 2018), computing a Pearson chi-square to detect significant differences across the groups (latent classes) obtained in Step 1. In the model, we test the difference across classes in the local governments' financial indicators as well as in the level of perceived effectiveness induced by service digitisation.

4 Results

Results from the model fit statistics are presented in Table 4. The BIC reports a minimum for a number of classes equal to 5. The LMR test indicates a non-significant p-value at 5 classes, hence pointing at a 4-class specification model. However, the p-value turns out to be significant again at 6 classes, indicating that the significance level of the 4-class model was due to a local optimum. Given the possible imprecision of the

LMR test in this model specification, and given that the literature suggests that the BIC provides better goodness of fit than the LMR test (Nylund et al., 2007), we selected a 5-class specification model, which has an entropy level of 0.875.

Table 4. Fit statistics for the latent class model.

Number of classes	AIC	BIC	LMR test (p-value)	Entropy
2	6890.49	6989.23	0.000	0.816
3	6278.18	6428.64	0.000	0.894
4	6124.41	6326.59	0.001	0.897
5	**6030.63**	**6284.53**	**0.497**	**0.875**
6	5988.13	6293.76	0.032	0.879
7	5952.54	6309.89	0.000	0.907

Note: AIC=Akaike information criterion; BIC=Bayesian information criterion; LMR=Lo-Mendell-Rubin likelihood ratio test. The p-value refers to the significance level of the LMR test.

The pattern of distribution of the 5 classes along the digitisation indicators is provided in Figure 2 . On the horizontal axis, we show the 10 indicators, while on the vertical axis we present the proportion of local governments within each group that reported having digitised the service. The first five indicators refer to G2C services, while the remaining five report G2B services.

(Insert here figure 2)

Of the 814 local governments included in the analysis, the largest group (36%) is made of *Non-digital*, meaning that more than one third of the local governments reported to have digitised basically none of the services (except for the event declaration service, digitised by less than 20% of the local governments). The second largest group is that of *Selective digital for companies* (30%) made up of local governments that have digitised a very restricted sample of services offered to companies. Most of these local governments digitised the requests for building renovation, while a smaller sample (nearly 70% within this cluster) digitised the request for building permits and event declaration (which is intended for organisations willing to set up fairs or other events temporarily). A third group of local governments is a higher-level categorisation than the previous one, labelled the *Digital for companies* group (16% of the sample). This cluster of local governments digitised the entire set of services offered to companies.

Only a small group of local governments (8%) digitised the services for the citizens only, namely the *Digital for citizens* group. In this case, the services targeted for digitisation are the requests for birth certificates, change of residence, or poll workers list. Within the G2C services, waste taxes and handicap placard request services have been digitised by respectively only 37% and 15% of the *Digital for citizens* local governments.

A final group was defined as *Digital for all* (10% of the observations), reporting a high level of digitisation of the services. Again, an exception is represented by the handicap placard request that remains the service subject to the lowest digitisation, which is still the highest for this group, being digitised by 36% of the local governments in this class. The low digitisation of the handicap placard is explained by the need to have a physical placard, thus high complexity in terms of fully digitising the service.

Results from Step 2 are given in Table 5, where each coefficient can be interpreted as the effect of the socio-economic and environmental variables on the likelihood that a local government belongs to a particular class in relation to the reference group, the *Non-digital* municipalities. Results show that only a few variables are associated with membership of a specific class/cluster, especially the population size and the income per capita. Indeed, the *Digital for all* and the *Digital for citizens* groups are more likely to have a larger population than the *Non-digital* group. The digitisation for companies seems instead to be driven by the economic background of the local government, given that local governments with larger income per capita are respectively 1.6 and 1.4 times more likely to be in the *Digital for companies* or in the *Selective digital for companies* groups. Moreover, the collaboration between local governments makes it 1.46 times more likely that a local government will be in the *Selective digital for companies* rather than in the *Non-digital* group, while local governments in mountain areas show a lower likelihood of digitisation.

Table 5. Coefficients, means and odds ratios for covariates predicting class membership.

	Digital for companies			Digital for all			Selective digital for companies			Digital for citizens			Non-digital
	Coef	*Odds ratio*	Mean	*Coef*	*Odds ratio*	Mean	*Coef*	*Odds ratio*	Mean	*Coef*	*Odds ratio*	Mean	Mean
Collaboration	*0.208*		0.26	*0.339*		0.27	*0.379**	*1.46*	0.30	*0.450*		0.28	0.27
Mountain	*-0.196*		0.38	*-0.477*		0.32	*-0.509***	*0.60*	0.36	*0.062*		0.41	0.50
Territory (North)	*0.562*		0.73	*0.877*		0.73	*0.165*		0.69	*-0.431*		0.60	0.55
Territory (Centre)	*0.637*		0.13	*0.690*		0.16	*-0.140*		0.10	*-0.386*		0.13	0.12
Population	*-0.059*		3.19	*0.295***	*1.34*	3.68	*0.136*		3.17	*0.306**	*1.36*	3.71	2.88
Density	*0.000*		462	*0.000*		572	*0.000*		515	*0.000*		434	418
Old citizens	*-0.471*		0.12	*0.213*		0.11	*0.044*		0.12	*0.256*		0.13	0.12
Young citizens	*0.002*		0.30	*-0.254*		0.31	*0.045*		0.31	*-0.083*		0.33	0.31
Income	*0.468**	*1.60*	€ 13,555	*0.403*		€ 14,161	*0.362**	*1.44*	€ 13,359	*0.511*		€ 14,226	€ 12,109
Companies	*0.000*		1557	*0.000**	*1.00*	1425	*0.000*		1398	*0.000*		650	842

*Note: Coefficients result from logistic regressions. *p≤.10. ** p≤.05. *** p≤.01. Odds ratios are reported for statistically significant correlation only and represent the effect of the predictors on the likelihood that one outcome will occur in relation to the reference category (Non-digital).*

Finally, the results from Step 3 are given in Table 6. In addition to the overall p-value, which suggests the presence of statistically significant differences between groups, the apexes show the group pairwise comparison, highlighting the significant differences group-by-group. The outcomes indicate the differences measured in terms of both efficiency and perceived effectiveness.

The *Non-digital* group shows the highest value of total current expenditures and total investments per inhabitant, indicating a lower degree of efficiency in expenditures. When accounting for the deviation from the average expenditure in local governments with a similar size, the difference in the investment per inhabitant is not statistically significant anymore, indicating the possible mediating role played by the size of the local government.

When observing the indicators of perceived effectiveness, a tendency towards more positive perceptions emerges in the *Digital for all* and the *Digital for citizens* groups. Hence, local governments digitising services for citizens perceive a more positive impact especially in terms of transparency, communication, and quality of service.

Table 6. Means and p-values for distal outcomes across groups.

		Digital for companies (1)	Digital for all (2)	Non-Digital (3)	Selective digital for companies (4)	Digital for citizens (5)	P-value (overall)
Total current expenditures per inhabitant	(a)	843.69	914.22	947.09 [5]	862.52	828.99 [3]	0.185
	(b)	0.70%	-0.3% [3,4]	4.1% [2]	3.4%[2]	0.70%	0.090
Total investment expenditures per inhabitant	(a)	244.51 [3]	203.95 [3]	342.84 [1,2,4,5]	237.50 [3]	224.05 [3]	0.050
	(b)	-19.20%	2.40%	-2.10%	-14.90%	-1.20%	0.341
Personnel expenditures on total current expenditures	(a)	0.154	0.149	0.162	0.164	0.158	0.370
	(b)	-3.90%	-7.3%[4]	0.50%	3.1%[2]	-2.40%	0.238
Perception of transparency		3.932	4.134[3,4]	3.773[2]	3.702[2,5]	4.029[4]	0.003
Perception of better communication with citizens		3.796	4.058[3,4]	3.699[2,5]	3.63[2,5]	4.055[3,4]	0.001

Perception of higher service quality for citizens and companies	$4.166^{3,4}$	$4.245^{3,4}$	$3.889^{1,2,5}$	$3.895^{1,2,5}$	$4.387^{3,4}$	0.000

Note: The p-value refers to the overall Chi-square test. Apexes report a statistically significant difference (p≤.05) between each group and the one indicated by the apex. (a) refers to the absolute value of the financial indicator; (b) refers to the deviation from the average value of that indicator in local governments within the same population cluster.

5 Discussion

Local governments can be divided into four categories based on their e-maturity level (Figure 3):

(1) Non-Digital: local governments with a low e-maturity level, corresponding to low or no digitisation of their services. Citizens and companies can access the service only via the physical counter.

(2) G2B-oriented: local governments that started digitising some services, focusing only or mainly on G2B services. Two classes that emerged from Step 1 of the LCA are included here, the *Selective digital for companies* and the *Digital for companies* groups.

(3) G2C-oriented: local governments focusing only or mainly on G2C services (*Digital for citizens* group).

(4) Fully digital: local governments with a high level of e-maturity, where the majority of services are available via digital channels, (*Digital for all* group).

(insert here figure 3)

The results add relevant evidence to an open debate, proposing a new lens for classifying e-maturity in local governments that complements the existing models, adding a classification that takes into consideration the different types of users (Yildiz, 2007). Local governments are complex organisations, whose maturity cannot be evaluated taking the entire set of services together. Services, in fact, have a varying degree of internal complexity, several users with different needs, and several actors involved in their delivery (Tangi et al., 2021). The empirical validation of the theoretical constructs is also a major contribution by this paper.

The heterogeneity in the number of local governments that belong to each category offers some further considerations (Figure 4). Local governments digitise G2B services more frequently. This evidence can be explained by the greater pressure that companies put on local governments for making digital services available, due to their larger frequency of service use and to a more advanced internal digitisation process that, in turn, triggers the need to "go digital" also when interacting with public administrations. Nevertheless, there is a small group of local governments that decided to focus on digitisation of G2C services. This evidence questions the concept of linearity related to the development of e-maturity (Andersen et al., 2020): local government can follow different paths, thus a non-linear digitisation process.

(Insert here figure 4)

We do not have information on the evolution of e-maturity over time, hence we do not know if the current level of digitisation is considered by the organisation as an end-state or as a step towards full digitisation. Despite being a snapshot of a moment in time, our results show that more than one-third of Italian local governments are on the bottom left-hand side of the matrix, therefore they have not started the digitisation process yet. This should stimulate reflection by the policy-makers on whether and how to prioritise digitisation in the political agenda. Policy makers should consider that, currently, the focus of municipalities is on G2B services, thus the digitisation of services for citizens should be prioritised or incentivised accordingly. Moreover, the current situation due to COVID-19 may have increased citizens' expectations in terms of digitisation, making a substantial reflection on this even more relevant.

Looking at Step 2, the first general evidence is that only part of the socio-economic and environmental factors have an effect on e-maturity. This result is partially in contrast with previous studies (Budding et al., 2018; Manoharan, 2013). In particular, the size of the local government and the income per capita are the most significant indicators. Thus, policy-makers should reflect on the prioritisation of actions supporting medium and small sized municipalities as well as economically depressed areas. Moreover, the 'mountain' and the 'collaboration' factors influence the choice of digitising G2B or G2C services. This will support the conception of e-maturity as a context-specific topic, an aspect often missing or criticised in the current body of literature on e-maturity (Andersen et al., 2020; Janowski, 2015).

The results from Step 3 are coherent with previous studies indicating that e-maturity makes it possible to raise effectiveness without clear effects on efficiency (Nam, 2019). In fact, the level of e-maturity seems to have only a slight effect on local government expenditures and exclusively when reaching a fully accomplished e-maturity, while it seems to bring a positive impact on perceived effectiveness. This is a key message as digitisation can be interpreted as being more at the service of effectiveness than efficiency. Moreover, the evidence seems to suggest that only when reaching a high e-maturity level there are some slight effects on efficiency, whereas the perceived effectiveness increase already when a sub-sample of services is digitised. This evidence also has an implication for policy-makers, who must take it into consideration when deciding if and to what extent they are going to digitise public services.

This is a novel result with respect to previous studies, where efficiency was rarely taken into consideration for a lack of a robust dataset or where no relation between e-maturity and efficiency was identified (Budding et al., 2018).

6 Conclusion and further research

In this article, we took into account two different sub-set of services (G2C and G2B) demonstrating the relevance of this distinction. Further research shall keep investigating in the same direction, looking at other types of services (for example G2G) or examining whether the macro-division proposed provides the optimal level of granularity for assessing e-maturity. Moreover, further research could adopt the same logic in different contexts such as different countries or different types of public organisations to explore the generalisability of our discussion.

When analysing the e-maturity determinants, we did not include organisational factors, due to a lack of available data. However, the fact that only part of the determinants included in this analysis was found to influence e-maturity leaves an open question for a better understanding of organisational factors (like political or managerial willingness to innovate or administrators' motivation) that may determine e-maturity.

Moreover, the use of effectiveness measures collected from the end-users instead of self-assessed by the municipalities would add an insightful finding to existing knowledge. Finally, despite the descriptive nature of the study, we are aware of the fact that the non-random selection of our respondents poses some limitations to the generalisability of its results.

Supplementary documents: Figure 1 and tables 1,2 and 3 can be found online at https://journals.sagepub.com/home/ras

References

Andersen KN, Lee J, Mettler T, et al. (2020) Ten misunderstandings about maturity models. In: *ACM International Conference Proceeding Series*, 2020, pp. 261–266. DOI: 10.1145/3396956.3396980.

Asparouhov T and Muthén B (2018) Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. *Mplus Web Notes Version 3* 21(2): 1–22.

Bertot JC, Jaeger PT and Grimes JM (2012) Promoting transparency and accountability through ICTs, social media, and collaborative e-government. *Transforming Government: People, Process and Policy* 6(1): 78–91.

Boudreau C and Bernier L (2017) The implementation of integrated electronic service delivery in Quebec: the conditions of collaboration and lessons. *International Review of Administrative Sciences* 83(3): 602–620. DOI: 10.1177/0020852315598215.

Budding T, Faber B and Gradus R (2018) Assessing electronic service delivery in municipalities: determinants and financial consequences of e-government implementation. *Local Government Studies* 44(5). Routledge: 697–718. DOI: 10.1080/03003930.2018.1473768.

Celeux G and Soromenho G (1996) An entropy criterion for assessing the number of clusters in a mixture model. *Journal of classification* 13(2):

195–212.

Cinite I, Duxbury LE and Higgins C (2009) Measurement of Perceived Organizational Readiness for Change in the Public Sector. *British Journal of Management* 20(2): 265–277.

Collins LM and Lanza ST (2010) *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences* (NW Hoboken.). John Wiley and Sons Inc. https://doi.org/10.1002/9780470567333

Coursey D and Norris DF (2008) Models of E-Government: Are They Correct? An Empirical Assessment. *Public Administration Review* 68(3): 523–536. DOI: 10.1111/j.1540-6210.2008.00888.x.

Das A, Singh H and Joseph D (2017) A longitudinal study of e-government maturity. *Information and Management* 54(4). Elsevier B.V.: 415–426. DOI: 10.1016/j.im.2016.09.006.

ISTAT (2010) *Information and Communication Technology in the local government administrations*. Retrieved from https://www.istat.it/it/files//2011/01/ICT_PA_2009_-EN.pdf

Jacob DW, Fudzee MFM, Salamat MA, et al. (2019) A review of the generic end-user adoption of e-government services. *International Review of Administrative Sciences* 85(4): 799–818. DOI: 10.1177/0020852319861895.

Janowski T (2015) Digital government evolution: From transformation to contextualization. *Government Information Quarterly* 32(3). Elsevier Inc.: 221–236. DOI: 10.1016/j.giq.2015.07.001.

Layne K and Lee J (2001) Developing fully functional E-government: A four stage model. *Government Information Quarterly* 18(2): 122–136. DOI: 10.1016/S0740-624X(01)00066-1.

Lee J (2010) 10 year retrospect on stage models of e-Government: A qualitative meta-synthesis. *Government Information Quarterly* 27(3). Elsevier Inc.: 220–230. DOI: 10.1016/j.giq.2009.12.009.

Lo Y, Mendell NR and Rubin DB (2001) Testing the number of components in a normal mixture. *Biometrika* 88(3): 767–778.

Lourenço RP (2015) An analysis of open government portals: A perspective of transparency for accountability. *Government Information Quarterly* 32(3): 323–332. DOI: 10.1016/j.giq.2015.05.006.

Manoharan A (2013) A Study of the Determinants of County E-Government in the United States. *American Review of Public Administration* 43(2): 159–178. DOI: 10.1177/0275074012437876.

Muthén B and Muthén LK (2000) Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical & Experimental Research* 24(6): 882–891.

Nam T (2019) Does E-Government Raise Effectiveness and Efficiency? Examining the Cross-national Effect. *Journal of Global Information Management* 27(3): 120–138.

Nasi G, Frosini F and Cristofoli D (2011) Online service provision: Are municipalities really innovative? The case of larger municipalities in Italy. *Public Administration* 89(3): 821–839. DOI: 10.1111/j.1467-9299.2010.01865.x.

Nylund KL, Asparouhov T and Muthén B (2007) Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidiscplinary Journal* 14(4): 535–569.

Samuelsen K and Raczynski K (2013) Latent Class/Profile Analysis. In: *Applied Quantitative Analysis in the Social Sciences*. New York: Routledge, pp. 304–328.

Scholta H, Mertens W, Kowalkiewicz M, et al. (2019) From one-stop shop to no-stop shop: An e-government stage model. *Government Information Quarterly* 36(1): 11–26. DOI: 10.1016/j.giq.2018.11.010.

Tan H, Zhao X and Zhang N (2020) Technology symbolization: political mechanism of local e-government adoption and implementation1. *International Review of Administrative Sciences*. Epub ahead of print 22 April 2021.DOI: 10.1177/0020852320915637.

Tangi L, Benedetti M, Gastaldi L, et al. (2021) Mandatory provisioning of digital public services as a feasible service delivery strategy: Evidence from Italian local governments. *Government Information Quarterly* 38(1). Elsevier Inc.: 101543. DOI: 10.1016/j.giq.2020.101543.

Weerakkody V, El-Haddadeh R, Sivarajah U, et al. (2019) A case analysis of E-government service delivery through a service chain dimension. *International Journal of Information Management* 47(August 2018). Elsevier: 233–238. DOI: 10.1016/j.ijinfomgt.2018.11.001.

West DM (2004) E-Government and the Transformation of Service Delivery and Citizen Attitudes. *Public Administration Review* 64(1). Wiley/Blackwell (10.1111): 15–27. DOI: 10.1111/j.1540-6210.2004.00343.x.

Wirtz BW and Daiser P (2018) A meta-analysis of empirical e-government research and its future research implications. *International Review of Administrative Sciences* 84(1): 144–163. DOI: 10.1177/0020852315599047.

Yildiz M (2007) E-government research: Reviewing the literature, limitations, and ways forward. *Government Information Quarterly* 24(3): 646–665. DOI: 10.1016/j.giq.2007.01.002.

Figure 2 : Patterns of digitisation across groups.

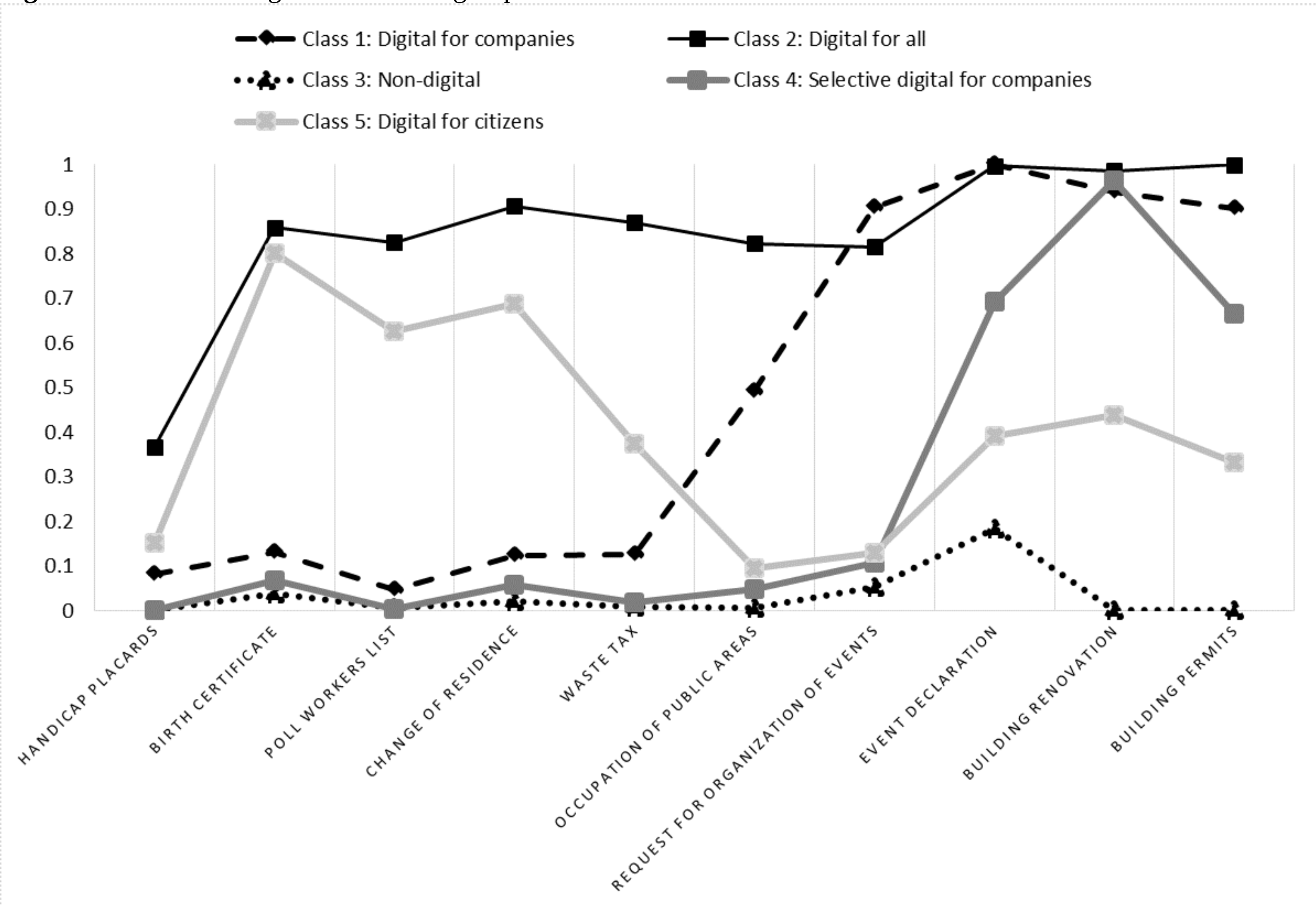


Figure 3: E-maturity model.

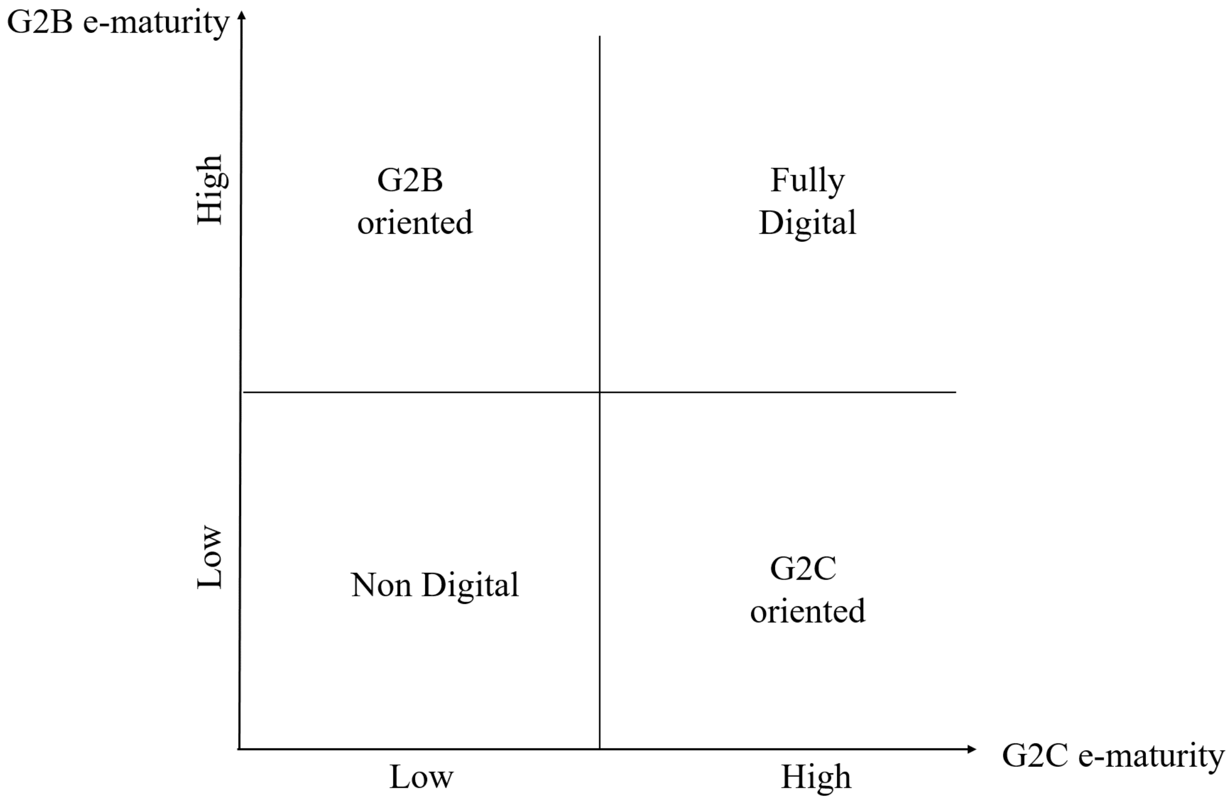
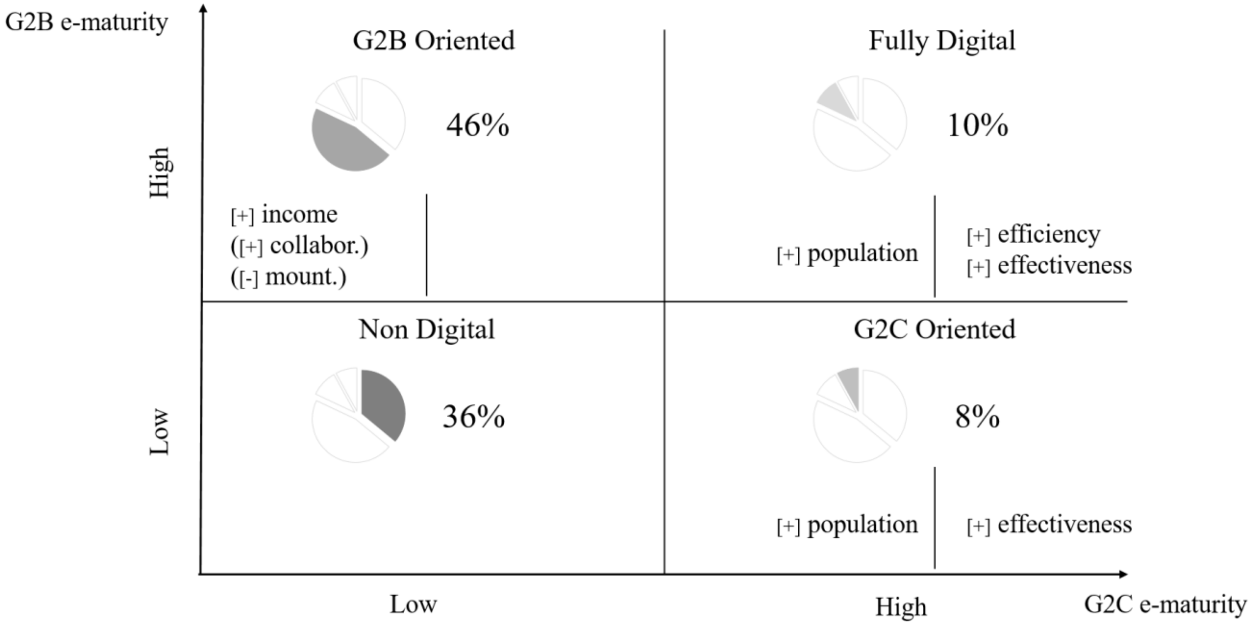


Figure 4. Percentage and characteristics of the local governments in each class.



Note: The factors reported in the figure are, in synthesis, those statistically significant. The sign indicates the direction of the relationship with respect to the reference category - the "Non-digital" class. On the bottom left, the socio-economic and environmental characteristics, on the bottom right, the performance dimensions. Collaboration and mountain for the G2B category are in brackets because they are significant only for part of the local governments included in the category, as it is composed by two different clusters emerging from the LCA.