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Determinants of E-Government Use in the European Union: An Empirical Analysis

Alexandra Lavinia Horobeț, Irina Mnohoghitnei, Emanuela Marinela Luminița Zlatea and Alexandra Smedoiu-Popoviciu *

Department of International Business and Economics, Bucharest University of Economic Studies, Piața Română 6, 010374 Bucharest, Romania; alexandra.horobet@rei.ase.ro (A.L.H.); mnohoghitneiirina20@stud.ase.ro (I.M.); zlateamarinela15@stud.ase.ro (E.M.L.Z.)

* Correspondence: smedoiupopoviciualexandra20@stud.ase.ro

Abstract: Efficient governments, defined as those that provide digital public services and effectively support their citizens through modern tools and channels, can be the result of a variety of factors, including education, urbanization, infrastructure, and economic growth as measured by GDP per capita. Existing research, however, has not provided a convincing answer to this question. At the same time, there is an undeniable increase in the availability and use of digital government services, with disparities in the range of services offered and access to infrastructure. Based on an empirical data set from 2008 to 2020, we propose an investigation into the determinants of e-government use in European Union countries. We use quantitative analysis based on the generalized method of moments (GMM) to explain why people use e-government. Furthermore, we substantiate the results found using the GMM methodology applied to panel data with Granger causality, which shows the contribution of variables to the current values of the other variables over time, highlighting the powerful influences between them. We discovered that education is the most important determinant factor for e-government use in the European Union, but there are some surprising findings, such as the negative correlation between internet use and e-government indicators, or the fact that a better government does not automatically result in economic growth. Rather, a developed country establishes the foundation for its citizens to use public services efficiently.

Keywords: e-government; government efficiency; education; internet use

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1. Introduction

Efficient digital public services, or e-government, can increase the transparency of administration, increase savings for businesses and governments alike, and facilitate more active participation in democratic practices [1]. While there are many studies aimed at deconstructing the relationship between a government and its citizens, it is still unclear which factors lead to the adoption of e-government services or the relationship between costs and benefits. From declining cash use and documenting economic transactions and interactions, to better collection of taxes and saving costs, and opportunity costs in terms of compliance, the e-government paradigm can accelerate economic growth [2].

A significant increase in the use of information technologies in government functions and procedures has become a relevant factor in society and economic activities but it is, of course, subject to the availability of the relevant infrastructure [3]. Therefore, our study largely documents the elements that need to be in place for an efficient e-government to exist.

The COVID-19 pandemic has accelerated governments' digital transformation, but different countries find themselves at very different stages in their digital journeys. In general, European countries have been early adopters of e-government, prompting the EU to commit to provide all key public services online by 2030 [4]. However, significant differences remain, in part due to disparities in funding and digital infrastructure, as well as political will more broadly. Some countries offer comprehensive e-government portals that cover healthcare access, taxation, or digital ID, while others only offer basic services such as online forms [5]. The European Commission [4] scores Estonia and Malta as the most mature, but some Eastern European countries score nearly half on the same scale. Estonia is often considered a world leader in e-government, not just because of its innovative solutions such as digital ID, but also because of its comprehensive online services for citizens and businesses alike [6].

To make the case, this paper uses an empirical dataset, based on European Union countries over the last decade, to determine the impact of education, internet use, government efficiency, as well as other relevant indicators, on the adoption of e-government. The methodology is based on the generalized method of moments (GMM) that aims to explain which factors influence e-government in selected European Union economies, over the period of 2008–2020. Moreover, we substantiate the results identified with the help of the GMM methodology, applied to panel data using Granger causality [7], that show the contribution of variables to the current values of the other variables over time, thus highlighting the powerful influences between them.

Our paper makes several important contributions to the literature. We decided to remove data older than 2020 despite, in some cases, this being available to ensure our analysis is not skewed by the COVID-19 global pandemic. To the best of our knowledge, this is the first paper showing an inverse relationship between internet access and uptake of e-government services. This could, in part, be explained by internet access alone not being sufficient for e-government adoption. Other factors such as digital literacy, trust in government, and the availability of online services may also play important roles in determining the uptake, as well as the overall functionality and quality of e-government services [8]. Furthermore, our paper adds to the limited body of existing research investigating the links between e-government uptake, education, and economic growth.

We find that overall levels of education have a clear impact on e-government adoption, but that levels of internet or mobile subscription, as well as of overall economic growth, does not. This important finding suggests that simply launching e-government solutions is not enough, even in the presence of supporting infrastructure. Instead, policymakers should focus on understanding what citizens need and how they engage with digital services, and tailor e-government services accordingly.

The next sections of the paper are structured as follows. We first provide a discussion of the most relevant findings in the extant literature, with reference to e-government and government efficiency, then we present the research methodology and the main findings. The Results and Discussion sections present the findings and address them, considering other relevant scholarly papers. The final section concludes, outlines the main limits of our research, and suggests directions for future research.

2. Literature Review

When we shed light on government reforms, it is important to bring consideration of what an essential component is to the foreground: efficiency. The relationship between a government and its citizens has already been empirically examined in many studies, but evidence is mixed, and it remains unclear how an efficient government can contribute to economic growth. Empirical analysis varies in terms of scope, considering the regional contexts, the models used and the examined periods, but government efficiency is generally found to positively impact the economy and the functioning of society, with beneficial implications for countries' economic growth and competitiveness. We discuss the most important and relevant findings of previous studies, which are also summarized in Table 1.

Table 1. Summary of extant literature on government actions and government efficiency.

Authors	Period and Region/Countries/ Entities Studied	Empirical Model	Main Input Variable(s)	Output(s)
Hauner and Kyobe [9]	1980–2004; 114 countries	Panel model	Education and health spending Years of schooling Income per capita	Government efficiency
Voghouei and Jamali [10]	2003–2010; 51 countries	Dynamic panel model—system-GMM	Information technology expenditure by government Total information technology expenditure in economy Consumer price index Transparency Corruption Ethnic fractionalization	Government efficiency (government spending as share of GDP)
Lizińska et al. [11]	2015–2016 1220 municipalities in Poland	Survey	Number of tasks actually implemented by local governments Number of tasks which could be implemented	Institutional efficiency of local governments
Balaguer-Coll et al. [12]	2009–2015; The Valencian Region	Robust order methodology	Population density Unemployed job seekers Disposable income Accommodation vacancies Political ideology of the incumbent party Herfindahl index Voter turnout in local elections Tax revenues Transfer revenues Indebtedness Number of mistakes in the budgetary statements	Index of (in)efficiency
Halaskova et al. [13]	2012–2015 and 2015–2018; 27 EU countries	Data envelopment analysis (DEA)	Local government expenditure by function	Government effectiveness Corruption perceptions Index
Wen et al. [14]	1996–2018; 166 countries	Panel data	Government efficiency Bureaucracy quality	Patents and trademarks
Ding et al. [15]	2002–2018; 156 countries	Panel data	Government efficiency	Health outcomes (disability-adjusted life years (DALYs))
Reinecke and Schmerer [16]	2001–2006; Chinese firms	Panel data regression	Government efficiency Firm age Sales State-owned enterprises Employment and capital stock Total factor productivity (TFP)	Export share on total output
Chen and Yoon [17]	2010–2016; A-share listed firms from 27 Chinese provincial government	2SLS regression	Administrative efficiency of local governments	R&D expenditure over total assets Number of patent applications

Table 1. *Cont.*

Authors	Period and Region/Countries/ Entities Studied	Empirical Model	Main Input Variable(s)	Output(s)
Amir and Gokmenoglu [18]	2002–2015; 31 OECD countries	Panel data model	Government efficiency Corruption Employment Population Urbanization	Financial development
Gupta and Verhoeven [19]	1984–1995; 37 countries in Africa	Free disposal hull (FDH) analysis	Education and health spending by the government	Life expectancy Infant mortality Immunizations against diseases School enrolment Adult illiteracy
Geys [20]	2000; Flemish region in Belgium	Stochastic parametric reference technology	Current expenditures in the municipality	Number of subsistence grants beneficiaries Number of students in local primary schools Public recreational facilities Length of municipal roads.
Liu et al. [21]	2007; 22 Local governments in Taiwan	Data envelopment analysis (DEA) model; Sharpe ratio.	Employment Accumulation of fixed assets	Real disposable income per capita Unemployment rate Volume of waste clearance Air pollution
Asatryan and De Witte [22]	2003–2011; German State of Bavaria	Fully non-parametric approach	Per capita expenditure	Pupil population Child population Elderly patient population Green and recreational areasEmployees paying social security
Chang et al. [23]	1990–2014; 31 OECD countries	Group-mean dynamic common correlated estimator (DCCE) panel regression Panel cointegration Vector-error-correction model (VECM)	Corruption, political ideology Real per capita GDP FDI Oil prices Electricity regulation Gas regulation	Energy intensity
Seo et al. [24]	2015–2016; 42 central administrative agencies in the Republic of Korea	Data envelopment analysis (DEA)	IT budget Number of employees	Number of policies for the adoption of Government 3.0 Number of open public data (API) Number of public services that can be applied for online

Table 1. *Cont.*

Authors	Period and Region/Countries/ Entities Studied	Empirical Model	Main Input Variable(s)	Output(s)
Alonso and Andrews [25]	2002–2008; local governments in the United Kingdom	Dynamic panel data model	Total per capita service expenditure, excluding expenditure on central administration.	Fiscal decentralization Fiscal deprivation Number of pupils attending the General Certificate of Secondary Education examination Older people being helped to live at home Waste management
Chen and Paudel [26]	2004–2017; 30 provinces in China	Malmquist–Luenberger index Dynamic panel model	Number of people employed by government Provincial-owned economic capital stock Annual financial expenditure.	GDP per capita Unemployment rate Consumer price index Ratio of middle school teachers to students Density of transportation infrastructure Number of hospital beds per capita Number of cases of corruption per 10,000 people Rate of labor dispute settlement
Pacheco et al. [27]	2008–2018; 324 Chilean municipalities	Parametric models and panel data	Expenditure on personnel Consumer goods and services Expenditure on education Expenditure on health Transfers to health services and centres Transfers to public education schools Municipality population Distance to the regional capital	Rural and urban municipal education establishments; Enrolment in municipal education establishments Health facilities Maintained green areas; Cleaning services, waste collection and landfill services Drinking water coverage Social organizations

Extant literature on the effects of government efficiency is abundant. For example, Balaguer-Coll et al. [28] showed that government efficiency in neighboring Spanish municipalities positively affects local government's own efficiency. Other OECD-focused studies strongly indicate that government efficiency, measured by employment, urbanization, and government spending, has a positive effect on financial development [18]. Greater government efficiency is also found to lead to a reduction in energy intensity by enhancing overall energy efficiency [23]. Clear links have also been established between government efficiency and democracy—for example, intense democratic activity which promotes competition is associated with higher efficiency in the provision of goods and services [22] while corruption is found to decrease government efficiency [18].

More recently, the literature has also turned to exploring the effects of e-government. For example, some studies have found that e-government efficiency positively affects the output and innovation investment by reducing rent-seeking opportunities, reducing bureaucracy, and improving the overall technological abilities of government staff [14,17]. Seo et al. [24] examined e-government efficiency in Korea and found citizen-centric IT service integration and IT investment to be key driving factors. Furthermore, Voghouei and Jamali [10] argue that government efficiency responds in a positive way to changes in information technology expenditure, whether in the government or in broader society. Moreover, in certain countries, government inefficiency sharpens the domestic technology gaps by providing inappropriate advantages to firms that are already well ingrained and leads to slower technology penetration rates [29].

More broadly, government expenditure is also widely used in conjunction with government efficiency. Individuals assess the 'price/quantity' of government policies by considering the level of spending on (or taxation for) public goods provision simultaneously with how much public goods they receive [20]. Hauner and Kyobe [9] underline that higher government expenditure relative to GDP tends to be associated with lower efficiency. On the other hand, improvements in educational attainment and health output are feasible by correcting inefficiencies in government spending on education and health [19]. Ding et al. [15] have also shown that increases in government efficiency can significantly improve health outcomes.

Government efficiency is not the only aspect that could be enhanced by e-government; education is another important factor [30]. Indeed, Horobet et al. [31] find that in the EU, education plays a key role both in digitalization and financial development, with no significant differences between Western and Eastern European economies. Cerna et al. [32] show that education has quickly adapted to the accelerated digitalization instilled by the COVID-19 pandemic, making it even more relevant when discussing its impact on digitalization.

Digitalization, measured by either internet use or number of mobile subscriptions, is key when discussing e-government [1]. DESA [33] finds that most UN countries have a national digital government strategy in place, and that in nearly all countries, people's as well as authorities' digital engagement has increased. In the long run, digitalization could lead to a paradigm shift towards a digital-first society, with new forms of digital money, enabling novel and more efficient ways of interacting with services [34,35]. However, the road ahead remains long. Spacek et al. [36] have shown that the level of digitalization in Central and Eastern European countries remains modest.

Dobrolyubova et al. [37] found no direct cause and effect relationship between the digitalization of government and other governance indicators such as effectiveness. Further, Ahmad et al. [38] show that many public services remain manual because their digital equivalent is inadequate, featuring blank web pages, invalid forms, or out of date information. This suggests that e-government involves more than just the tools that allow citizens to interact with their governments in digital form; it also involves rethinking processes so that they can become digital-first and making interaction with government easier, cheaper, and quicker [1]. Indeed, Mensah et al. [39] and Chen et al. [40] conclude that the use of e-government services is not predicted by the performance, effort, or social influence but instead by the perceived service quality and trust in government.

Several studies that associate local authorities' efficiency with state government efficiency as a whole, because of its positive influence on the competitiveness of a country. In this regard, Liu et al. [21] find that the operating performance of local governments has a strong influence on a country's competitiveness. Additionally, the paper of Reinecke and Schmerer [16] highlights a positive correlation between firm size and export shares, as stimulated by high governmental efficiency. In fact, it stands out that larger firms in provinces with more efficient provincial governments have higher export rates. When it comes to the population, Chen et al. [26] demonstrated that an improvement in government efficiency in the urban area can increase the urban population. When considering other perspectives, EU countries' efficiency appears to be more strongly linked to their effectiveness than the overall perception of corruption [13].

Some studies have revealed that many local governments do not fully apply the available tools to streamline the provision of administrative services [11]. When it comes to fiscal decentralization, it is positively related to productive efficiency, but there is a negative relationship between socioeconomic deprivation and efficiency [25].

3. Research Methodology

E-government is a relatively new concept and because of this research on the drivers behind it, it remains scarce. Our paper aims to fill this gap by employing a GMM model and Granger causality to explain what lies behind e-government adoption. Extant literature shows there is little commonality across e-government implementation in European [13,41], and indeed global [9,10], regions and for this reason, we decided not to pursue more granular geographical data. We focused on EU countries because this is where we thought our research could bring the most value.

Panel regression models were chosen to identify the relationships between variables based on our research objectives and the characteristics of our data. As identified in the theoretical and empirical literature, these models have several characteristics that have transformed them into a robust econometric tool: the ability to handle heterogeneity, to work with smaller samples, to allow for more degrees of freedom, and to provide more efficient estimates when measuring the relationships between phenomena [42–44]. The dynamic panel model implemented in the GMM (generalized method of moments) framework, according to Blundell et al. [45] and Roodman [46], is better adapted to unbalanced panels and provides more robust estimations in the presence of many endogenous variables, while overcoming the issue of omitted dynamics encountered in static panel models.

We estimated the parameters in our dynamic panel models using the equation below:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 \theta_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the dependent variable—an e-government variable, Y_{it-1} indicates the one-year lag of the dependent variable, X_{it} is the main regressor—an education variable, and Z_{it} is the vector of control variables, aimed at controlling for the omitted variable bias. β_0 to β_4 are the parameters to be estimated, θ_{it} denotes specific country's fixed-effects, and ε_{it} is the error term with zero-mean. All variables were selected building on existing research and are presented in Table 1. The data cover all EU-27 countries between 2008 and 2020 and were collected from the sources indicated in Table 2.

Table 2. Variables description.

Variable	Notation	Definition	Source
Dependent variables			
Interaction with public authorities through the internet	EINTER	Individuals that used the internet for interaction with public authorities (last 12 months). The interaction refers to the use of at least one of the following services: (i) obtaining information from public authorities' websites; (ii) downloading official forms; (iii) submitting completed forms. In percentage of total individuals	Eurostat
Obtaining information from web sites of public authorities	EINFO	Individuals that obtained information from public authorities' websites (last 12 months). In percentage of total individuals	
Downloading official forms from the internet	EDOWNL	Individuals that downloaded official forms from public authorities' websites and/or portals (last 12 months). In percentage of total individuals	
Submitting completed forms through the internet	EFORMS	Individuals that submitted official forms using public authorities' websites and/or portals (last 12 months). In percentage of total individuals	

Table 2. *Cont.*

Variable	Notation	Definition	Source
Independent variables (main regressor and control variables)			
Education	EDI	Education index, as a component of the Human Development Index (HDI). Calculated as a simple geometric average of the mean years of schooling and the expected years of schooling (Klugman, 2011). In points	United Nations Development Program (UNDP)
Internet use	INTUSE	Internet use by individuals. Percentage of total population	Eurostat
Economic development	GDPC	Real gross domestic product per capita. In Euros	
Urbanization	URB	Population living in urban areas. In percentage of total population	
Government effectiveness	GOVEFF	Perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. In points	World Governance Indicators, World Bank

We considered two implementations of Equation (1), which differ in terms of the control variables included: first, we estimated the model by including only INTUSE, URB and GDPC in the control variables vector Zit, and then we added GOVEFF to the package of control variables. This approach allowed for a better understanding of the impetus that improved public service quality may provide for e-government development, in addition to the better-studied influence of education when internet access, urbanization, and economic development are considered. Specifically, the eight estimated models are the following:

$$\text{Model 1}: \ EINTER_{it} = \beta_0 + \beta_1 EINTER_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 \theta_t + \varepsilon_{it} \quad (2)$$

$$\text{Model 2}: \ EINTER_{it} = \beta_0 + \beta_1 EINTER_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 GOVEFF_{it} + \beta_7 \theta_t + \varepsilon_{it} \quad (3)$$

$$\text{Model 3}: \ EINFO_{it} = \beta_0 + \beta_1 EINFO_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 \theta_t + \varepsilon_{it} \quad (4)$$

$$\text{Model 4}: \ EINFO_{it} = \beta_0 + \beta_1 EINFO_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 GOVEFF_{it} + \beta_7 \theta_t + \varepsilon_{it} \quad (5)$$

$$\text{Model 5}: \ EDOWNL_{it} = \beta_0 + \beta_1 EDOWNL_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 \theta_t + \varepsilon_{it} \quad (6)$$

$$\text{Model 6}: \ EDOWNL_{it} = \beta_0 + \beta_1 EDOWNL_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 GOVEFF_{it} + \beta_7 \theta_t + \varepsilon_{it} \quad (7)$$

$$\text{Model 7}: \ EFORMS_{it} = \beta_0 + \beta_1 EFORMS_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 \theta_t + \varepsilon_{it} \quad (8)$$

$$\text{Model 8}: \ EFORMS_{it} = \beta_0 + \beta_1 EFORMS_{it-1} + \beta_2 EDI_{it} + \beta_3 INTUSE_{it} + \beta_4 GDPC_{it} + \beta_5 URB_{it} + \beta_6 GOVEFF_{it} + \beta_7 \theta_t + \varepsilon_{it} \quad (9)$$

System-GMM was used to estimate model parameters in Stata 17.0, following the methodology of Arellano and Bover [47], and Blundell and Bond [48]. We chose system over difference-GMM because it is more robust with regard to endogeneity in regressors [49,50], bias, and root mean error [51], and can address the weak instruments problem encountered in difference-GMM estimations [48]. According to Roodman [46], system-GMM estimators were found to properly handle potential heteroscedasticity and autocorrelation at the cross-sections level, particularly the two-step estimator. Furthermore, as evidenced by numerous empirical studies, the system-GMM is more effective when applied to panels with small time versus large cross-section dimensions [31,52]. Taking these arguments into account, we estimated the models using the two-step system-GMM estimator, but we also used the iterate GMM estimator proposed by Hansen et al. [53], which eliminates the arbitrariness associated with the initial weighting matrix selection [54]. Furthermore, the iterated system-GMM checks the robustness of the findings identified using the two-step system-GMM.

The estimations were carried out in Stata 17.0 using the GMM linear dynamic panel data estimation command "xtdpdgmm" [55], which incorporates Windmeijer's finite-sample standard error correction [56]. The "collapse" feature was used to limit instrument proliferation when implementing the estimation. The reliability of the estimates was validated using the Arrellano–Bond test for serial correlations of second-order in residuals [57] and the Sargan–Hansen test for overidentifying restrictions [58,59].

We supplemented the system-GMM estimates of the relationship between e-government development in EU countries and education with a causality test based on the Granger approach [7], which determines whether adding lagged values of an independent variable to past values of the dependent variable can provide a better explanation of the current value of the dependent variable. When this occurs, the independent variable is said to "cause" the dependent variable; however, it is important to note that this is not causality in the common sense of the term, but rather an assessment of predictability provided by the independent variable to the dependent variable. The Granger causality test is well-known among social science scholars and has previously been used in papers addressing governmental activities in panel frameworks [60–65]. The Granger causality test was carried out using Eviews 12. In all estimations, the variables were entered as logarithms, which means that the regression coefficients may be interpreted as elasticities.

4. Results and Discussion

4.1. Descriptive Statistics

Table 3, we present the mean, median and standard deviation, as well as sample characteristics (skewness, kurtosis, Jarque–Bera normal distribution test, and probability) of both dependent variables and independent variables used in our research methodology, cumulative for the period under analysis (i.e., 2008–2020). Both the dependent and the independent variables are quite consistent between the countries, based on the relative results of data homogeneity tests, which was not totally unexpected since European Union countries are quite similar in many respects. Except for EDI, where standard deviation is close to 0, thus indicating that most of the data is close to the mean, for the other variables, the relatively high standard deviation indicates that most of the data points are above or significantly above the mean, probably as a result of the presence of outliers. The data set is also symmetrical, given the values of skewness close to 0.5/−0.5. The kurtosis values show that the data may not be normally distributed and the distribution is rather peaked.

Table 3. Descriptive statistics.

Statistics	EINTER	EINFO	EDOWNL	EFORMS	EDI	INTUSE	GDPC	URB	GOVEFF
Mean	46.782	41.720	29.250	27.550	0.841	76.655	25,486.600	71.737	1.092
Median	47.940	42.360	28.050	24.210	0.843	79.260	20,770.000	69.565	1.065
Max	91.670	89.510	73.700	76.590	0.943	97.850	86,330.000	98.041	2.241
Min	4.930	4.300	2.750	1.890	0.688	36.600	4970.000	52.209	−0.372
Standard deviation	19.940	18.599	14.185	17.910	0.055	13.637	16,965.000	12.264	0.578
Skewness	0.151	0.320	0.474	0.890	−0.114	−0.592	1.509	0.257	−0.189
Kurtosis	2.368	2.750	2.780	3.085	2.093	2.814	5.860	2.146	2.339
Jarque–Bera	6.320	6.064	12.210	40.868	11.266	18.463	222.542	12.795	7.465
Probability	0.042	0.048	0.002	0.000	0.004	0.000	0.000	0.002	0.024

Source: Authors' computations using statistical software.

4.2. Model Estimates

Table 4 shows the results of the two-step system GMM-estimates for the four dependent variables. For each dependent variable, two models were implemented: one that uses only education (EDI), internet use (INTUSE), economic development (GDPC), and urbanization (URB) as control variables, and another one that adds government efficiency (GOVEFF). This approach allowed us to detect the contribution of a good perception of citizens about the ability of government to provide efficient services to the development of e-government.

Table 4. Results of two-step system-GMM.

Variables-Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Dependent variable	EINTER		EINFO		EDOWNL		EFORMS	
EINTER—1 lag	1.102 *	0.985 *	--	--	--	--	--	--
EINFO—1 lag	--	--	0.992 *	0.992 *	--	--	--	--
EDOWNL—1 lag	--	--	--	--	0.979 *	0.928 *	--	--
EFORMS—1 lag	--	--	--	--	--	--	0.943 *	0.909 *
EDI	0.282 ***	0.150 ***	0.385 ***	0.202 ***	0.393 **	0.202	0.368	0.185
INTUSE	−0.336 ***	−0.259 ***	−0.345 ***	−0.239 **	−0.441 *	−0.305 *	−0.199	−0.117
URB	0.065	0.083 ***	0.08	0.104 ***	0.113 **	0.133 *	0.113 **	0.153 **
GDPC	0.004	−0.029 **	0.006	−0.043 ***	0.037	0.006	0.009	−0.051 ***
GOVEFF	--	0.070 **	--	0.085	--	0.084 **	--	0.133 *
Constant	1.171	1.175 **	1.237 **	1.494 *	1.246 **	0.991 *	0.617	0.731
Observations	284	284	282	282	282	282	282	282
AR(2)	0.211	0.184	0.175	0.149	0.089	0.086	0.861	0.865
Sargan–Hansen statistic	0.166	0.313	0.090	0.150	0.245	0.396	0.51	0.745

Note: *, ** and *** denote statistical significance at 1%, 5% and 10% level, respectively. The table reports *t*-tests and corresponding *p*-values. Source: Authors' computations using statistical software.

We found that education positively impacts the level of e-government development, as indicated by the positive regression coefficients in all models and their statistical significance for models where EINTER, EINFO and EDOWNL are dependent variables. A 1% increase in the Education Index (EDI) leads to 0.15–0.39% increases in e-government development, depending on the proxy used for the latter. This result is consistent with the existing literature, which has found that generally, people with higher education have a higher degree of use of government services provided in an efficient manner [66]. However, spillover effects from other variables can also be present—for example, EDI is also a determinant of GPDC, which can in turn lead to increased internet usage and better infrastructure and, thus, the circle of virtue reinforces itself. For people to be able to interact with their government digitally, a higher level of digital literacy is required, as people need to be able to use technology to, in the first instance, access the internet [30]. Furthermore, Yera et al. [67] observed that citizens with higher levels of education are more likely to make full use of available e-government tools, where they are available. Horobet et al. [31] further highlighted the importance of education in retraining workforces to be able to adapt to a more digital world.

At the same time, there is a negative association between internet use and the dependent variables pertaining to e-government—a 1% improvement in internet use (as the percentage of individuals that use the internet) leads to a 0.24–0.44% decline in e-government development, depending on the dependent variables used. This is a rather surprising result, as generally, it would be expected that access to internet and relevant infrastructure would be determinant for usage and thus, government efficiency. Thus, the more access EU citizens have to the internet, the less they appear to engage with e-government services, even when these are available. We believe this to be, at least in part, explained by the lack of real functionality some of the available e-government services offer. The more people are accustomed to the internet, the more they are likely to recognize when digital services are not up to standard. This intuition is covered by the extant literature, for example, Mensah et al. [39], Ahmad et al. [38], Chen et al. [17]. Another potential explanation is that the mere existence of infrastructure is not sufficient for people to efficiently interact with their government and that infrastructure may be the first step in a series of steps to be taken for an effective e-interaction between a government and its citizens. A perceived lack of trust may affect the relationship between citizens and their governments, both online and offline.

Urbanization is a factor that positively influences the development of e-government in EU-27 countries, confirming the expectation that urban populations are more eager to adopt online services, given their generally higher incomes and propensity to use ICT compared to rural populations. Thus, the regression coefficients are positive and statistically significant in six out of the eight models reported in Table 3, indicating that a 1% increase in urbanization leads to an increase in e-government from 0.0008 to 0.15%, depending on the explained variable. Nam [68] and Gerpott and Ahmadi [69] also found a positive correlation between the share of urban population and e-government services in the United States and Germany, respectively. On the other hand, since EU countries enjoy high rates of urbanization—the mean for our sample is 71.8% and the median is 69.7% over the 2008–2020 perioda favorable influence of urbanization on the adoption of e-government practices by EU countries' governments is to be expected.

With regard to economic development, proxied by real GDP per capita (GDPC), panel regression coefficients were either positive or negative, but the statistically significant ones were negative, indicating that a 1% increase in GDPC is associated with a 0.0029–0.0051% decline in e-government. What is interesting is the appearance of statistical significance for GDPC occurs only when government efficiency (GOVEFF) is included in the model. In the case of GOVEFF, the panel regression coefficients are all positive and statistically significant, indicating that a 1% increase in GOVEFF further stimulates e-government in a range of 0.007 to 0.13%. This is perhaps the most surprising of the results, since an effective government is expected to be able to serve its citizens with lower costs. Unfortunately, there are no data available about the cost of government efficiency to test this hypothesis. We consider this to be in line with the conclusions of Zhao et al. [70] who found that economic status, measured by GDP per capita, is not a significant predictor of e-government development at a global level, while contradicting evidence that shows the positive impact of higher economic development on the advancement of technology-powered government services [71,72]. As for the expected result of a positive influence of government efficiency on e-government development, we see it as a confirmation of the enhancement of the efficiency and effectiveness of providing government services by the use of e-government practices and vice versa, as suggested by previous research [61,73].

We continued our analysis with an improved, iterated-system GMM estimation, which has a practical advantage over the two-step estimator in that the results are invariant with respect to the scale of the data and to the initial weighting matrix. The results of the iterated-system GMM are presented in Table 5.

The results of the iterated system-GMM model reinforce the positive connection between the education index (level) and e-government development, regardless of latter's measurement, although statistical significance was found only for EINTER and EDOWNL. In this approach, the statistically significant coefficients' values do not depart from the findings in the two-step system-GMM estimation, providing a robustness check for our previous findings. Moreover, the iterated system-GMM provided robustness for our results on the positive influence of urbanization on e-government, given all positive coefficients and the statistical significance of half of them; furthermore, the range of coefficient values in the iterated system-GMM estimation is close to the range of coefficients in the two-step estimation, offering supplementary validation for our findings.

Table 5. Results of iterated system-GMM estimates.

Variables-Model	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Dependent variable	EINTER		EINFO		EDOWNL		EFORMS	
EINTER—1 lag	0.658 *	0.974 *	--	--	--	--	--	--
EINFO—1 lag	--	--	0.589	1.000 *	--	--	--	--
EDOWNL—1 lag	--	--	--	--	0.931 *	0.905 *	--	--
EFORMS—1 lag	--	--	--	--	--	--	0.928 *	0.912 *
EDI	0.157	0.163 **	−0.152	0.191	0.416 **	0.245	0.377	0.22
INTUSE	0.441	−0.231	0.554	−0.317 **	−0.376 **	−0.261 **	−0.179	−0.145
URB	0.061	0.091 ***	0.06	0.089	0.104	0.144 *	0.114 ***	0.153 **
GDPC	−0.007	−0.030 **	−0.061	−0.040	0.048	0.011	0.009	−0.045
GOVEFF	--	0.067 **	--	0.069	--	0.081 ***	--	0.212 **
Constant	−0.719	1.077 **	0.852	1.454 *	1.063 ***	0.787 ***	0.585	0.781 ***
Observations	284	284	282	282	282	282	282	282
AR(2)	0.232	0.171	0.277	0.137	0.101	0.088	0.859	0.864
Sargan–Hansen statistic	0.368	0.345	0.125	0.182	0.327	0.456	0.604	0.780
Convergence steps	34	22	65	27	33	26	17	17

Note: *, ** and *** denote statistical significance at 1%, 5% and 10% level, respectively. The table reports *t*-tests and corresponding *p*-values. Convergence steps show the number of iterations required to fine-tune the weighting matrix. Source: authors' computations using statistical software.

Moreover, there is a strong negative association between internet use and the dependent variables, as in the case of the two-step system-GMM estimation, which confirms that access to infrastructure is not a significant enough factor to determine use of online government services. On the other hand, the relationship between economic development (GDPC) and e-government is inconclusive in the iterated system-GMM estimation, as coefficients are both positive and negative, and there is statistical significance associated with the coefficient in only one model (Model 10). This finding opens the door to more research on the link between economic development and the use of online government services, particularly building on the very successful experience of EU countries with lower GDPCs (compared to the average EU level) that are already a recognized model for e-government, such as Estonia [74].

In the case of government efficiency, the iterated system-GMM estimation offers the validation of results in the two-step system-GMM, showing that higher government efficiency may provide the needed trust among citizens regarding the use of e-government services. On the other hand, the panel regression coefficient when EINFO—the percentage of individuals that obtained information from public authorities' websites—is the dependent variable is not statistically significant, which may correlate with the mixed findings in the existing literature [10,14]. This may be explained by the inconsistency in measuring e-government adoption [41] and thus, research results may not be directly comparable, or it may be that government efficiency is a pre-requisite rather than a consequence of an efficient government. Governments should therefore consider their digital strategies very carefully to ensure that the needs and wants their citizens in their interactions with authorities is mirrored by e-government offerings. Without customer acceptance and uptake, even when the much-needed infrastructure is in place, e-government solutions will struggle to reach their true potential. Given that education plays an important role in e-government, computer literacy is essential and should be available early on.

Last but not least, the findings in both GMM estimations show that there is persistence over time in the e-government variables, as all coefficients for the 1-year lagged values of the four e-government variables are statistically significant. Moreover, since these coefficients are positive, this indicates that e-government development reinforces itself, and once the level of online services provided by the governments is substantial enough, it tends to consolidate over time.

As for the consistency of our estimates, we verified them using the Arrellano–Bond test for serial correlations of second-order in residuals and the Sargan–Hansen test for overidentifying restrictions—the results of these tests are reported in Tables 5 and 6. In both estimations (two-step and iterated GMM), the tests confirm the lack of second-order serial correlations in the error terms (AR(2) above 0.05) and the validity of the instruments (Sargan–Hansen statistic above 0.05) for all our models.

Table 6. Stationarity tests.

	EINTER	EINFO	EFORMS	EDOWNL	EDI	INTUSE	GDPC	URB	GOVEFF
Level									
Levin, Lin, and Chu t	8.35	6.89	7.79	5.67	−6.41	8.64	6.01	1.03	−1.69
ADF—Fisher Chi-square	3.90	7.46	5.58	9.22	125.15	6.03	11.52	40.13	62.42
PP—Fisher chi-square	2.13	5.30	1.81	5.01	252.51	3.01	21.75	37.61	69.03
First difference									
Levin, Lin, and Chu t	−11.47	−13.84	−10.04	−11.76	−8.99	−6.83	−7.868	−0.59	−11.59
ADF—Fisher chi-square	188.66	218.09	162.36	205.70	149.75	119.56	122.48	115.46	183.56
PP—Fisher chi-square	322.45	379.82	260.70	360.04	210.38	174.80	237.85	155.46	298.52

Source: authors' computations using statistical software.

Given these results, we next went on to test for Granger causality in our panel dataset. First, we present in Table 6 the panel stationarity tests for our variables. The results show that all variables are stationary in the first difference, hence we proceeded to the implementation of the Granger causality test using the first differences.

The results of the Granger causality test are presented in Table 7. According to the Granger causality test, there are statistically significant causalities between the variables used in our analysis, which supports their inclusion in our models. Thus, we noticed the identified bi-directional Granger causality between the e-government variables (EDOWNL, EINFO, and EFORMS), which suggests that the various forms through which the government provides online services are connected and may enhance each other, ultimately providing citizens with an improved experience in using them. Moreover, government efficiency is identified as an important driver of e-government development, as GOVEFF unidirectionally causes (in terms of Granger causality) all e-government variables except EFORMS. Additionally, there is significant causality from GDPC to e-government variables, but also to education (EDI), which substantiates the essential role of economic development for an efficient government. In this framework, it is highly interesting that there is significant causality between INTUSE and GDPC, which shows that at the EU level, digitalization and the use of the internet are already important factors for economic development. At the same time, our findings show that a strategy to increase the overall government efficiency acts as a strong impetus to e-government.

Table 7. Results of panel Granger causality test.

	EINTER	EINFO	EDOWNL	EFORMS	EDI	INTUSE	URB	GDPC	GOVEFF
EINTER	--	0.576	4.645 *	3.500 **	1.587	0.083	0.348	0.487	2.337
EINFO	1.922	--	3.958 **	4.966 *	2.731	0.068	0.037	0.195	1.662
EDOWNL	0.929 *	7.970 *	--	4.573 **	1.276	1.883	0.080	1.585	0.984

Table 7. *Cont.*

	EINTER	EINFO	EDOWNL	EFORMS	EDI	INTUSE	URB	GDPC	GOVEFF
EFORMS	6.280 *	4.976 *	1.711	--	1.811	0.672	1.019	1.456	1.332
EDI	0.366	0.612	1.626	0.809	--	0.808	1.287	0.996	1.901
INTUSE	6.987	4.172	1.871	1.148	0.831	--	0.189	1.016 *	0.299
URB	0.642	1.428	1.738	0.847	0.836	0.281	--	1.777	1.805
GDPC	5.855 *	2.934	3.071 **	1.965	3.119 **	0.175	1.552	--	0.187
GOVEFF	49.481 *	40.759 *	3.081 **	0.844	1.848	0.388	3.589 **	2.167	--

Note: the table shows the F-statistic and its statistical significance (* and ** denote statistical significance at 1% and 5% levels, respectively) for the null hypothesis "the variable on the line does not Granger cause the variable on the column". Source: authors' computations using statistical software.

5. Conclusions

In this paper we aimed to determine the relationship between government efficiency, as measured by access to e-services, e-forms, public websites, etc., and variables denoting the level of development of a country: education, urbanization, internet and mobile use, GDP per capita. Our paper adds to the limited body of existing research by concluding that education is a very good determinant of government efficiency.

The results provided by the panel system-GMM estimation and the Granger causality test are mixed with regard to providing relevant infrastructure, which may mean that infrastructure is a pre-requisite but not a main determinant once a critical level has been reached. Additionally and surprisingly, a better government does not automatically create economic growth as measured by GDP per capita. Rather, it is the other way around: a richer country engenders trust in its citizens, which enables their use public services in an efficient way. More research on this topic would be welcome. Additionally, research could be targeted to specific age groups; for instance, for those over 54 years, INTUSE is lower than among other age groups, but it is unclear if this can be compensated for by other factors such as EDI and URB.

Our results could support future EU e-government policy decisions in several ways. Firstly, our findings highlight the importance of both education as a determinant of government efficiency and also the rethinking of government strategies for providing services to citizens, and the user experience when interacting with government services. These require the support of the needs of those with low digital skills, or those living in areas with poor or no internet access. Alternatively, as research suggests, more investment in education can create a level playing field. Furthermore, as highlighted by the [1], adequate e-government solutions should integrate all government services under a single, intuitive umbrella. This would help better align the take-up of e-government services with internet access and education.

One significant limitation of our research has been the identification of reliable data sources for quantifying the take-up of government digital services. For this reason, we limited our research to the EU, but for future research, it would be useful to develop a global framework for benchmarking interactions with e-government services. Since the only significant determinant seems to be education, future research could be directed towards analyzing several other variables that might help governments progress with their e-agenda.

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