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Algorithmic Interaction in Public Administration

Data-Based Communication and Political Participation in Public Institutions

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Abstract: This study investigates the influence of algorithmic interaction on public relations and political participation within public institutions. Digitalisation transforms traditional forms of communication, emphasising data-driven, transparent and accountable structures. The study uses OECD, Eurostat and World Bank data to create a balanced panel dataset for the EU27 countries from 2015 to 2024. Panel regression, causality tests, cointegration analyses and dynamic panel methods were applied. The findings suggest that social media use enhances e-government participation and that these interactions strengthen digital democracy. Furthermore, renewable energy and energy dependency have indirect relationships with digitalisation. The study justifies and stress-tests a proxy for algorithmic content density, documenting dynamic effects using System GMM with transparent instrument reporting. Subsample and interaction analyses reveal heterogeneous returns for OMS versus NMS. Policy recommendations emphasise algorithmic transparency, inclusive access and ethics by design.

Keywords: algorithmic interaction, public administration, political participation, digital governance, e-government

1. Introduction

Digital transformation is restructuring traditional public relations practices in public institutions. With digitalisation, the technology-driven approaches guide public–citizen interactions through data-based and algorithmic frameworks. This process is expected to reduce information asymmetry and increase transparency in processes (Alon-Barkat & Busuioc, 2024; Haug et al., 2024). However, algorithmic decision support systems are a technical innovation and a catalyst for new debates on political legitimacy, participation and accountability. In this process, public communication is shaped by data flows, automated classifications and feedback loops (Issar & Aneesh, 2022; Yukhno, 2024; Grimmer et al., 2022). In this process, institutions aim to strengthen the legitimacy of policies by processing citizen feedback more quickly using data analysis-based tools. However, this transformation also poses risks, such as digital inequality and access restrictions. Due to issues such as the digital divide or digital literacy, some citizen groups may be unable to participate in these systems (Yang et al., 2024; Djatmiko et al., 2025). Furthermore, bias and transparency issues in algorithmic decision-making processes increase the importance of trust-based interaction in public administration. In this context, public institutions should consider algorithmic communication not only a technical application but also a political practice (Mahroof et al., 2025; Bruun, 2024; Canel & Luoma-Aho, 2018; Herwix et al., 2022). Therefore, when designing data-based communication systems, public institutions must consider mechanisms that facilitate the transformation of participation processes.

Algorithms not only change the content landscape of public institutions, but they also reshape forms of political participation. This transformation presents both serious risks and new opportunities in state–citizen interactions. For example, public institutions can rapidly classify and process citizen feedback thanks to algorithmic systems. However, this process also paves the way for the systematic reproduction of biases, as discussed by Cordella & Gualdi in their concept of "algorithmic formalisation" (Cordella & Gualdi, 2025; Zuiderwijk et al., 2021; Busuioc, 2021; Wirtz et al., 2019). Experimental studies by Alon-Barkat and Busuioc (2023) have revealed that public officials can over-trust algorithmic recommendations (automation bias) or accept recommendations when their content aligns with their own prejudices (selective adherence). In public decision-making processes, algorithms are not merely technical tools but a mechanism through which democratic values are tested. Moreover, nowadays, political participation is driven by algorithmic recommendations and filters on digital platforms (Canel & Luoma-Aho, 2018; Herwix et al., 2022). Thus, visibility limits set by algorithms can limit citizen participation in public debates, increasing content inclusivity but also potentially excluding certain groups.

Algorithms are not only transforming the content presentations of public institutions, but big data analytics are also transforming the transparency and accountability dimensions of public communication. Public institutions can enhance their effectiveness in policymaking processes by analysing citizen behaviour using this data. Though biases and privacy issues in data processing can threaten democratic legitimacy (Ulbricht & Yeung, 2022). Grimmelikhuijsen & Meijer (2022) argue that algorithmic decision-making processes threaten the legitimacy of input, process and output (cf. Kassen, 2018). In contrast, König (2024) emphasises that citizens must choose between effectiveness and transparency in public algorithms. Purves and Davis (2022) have demonstrated that opaque algorithms in public institutions can undermine trust, and Andrews et al. (2022) have proposed an ethical and trust framework for AI applications in the public sector, highlighting ways to increase the legitimacy of these systems. In this context, transparency policies require explaining data access and the functioning of algorithms. Notably, OGP/Algorithmic Transparency projects aim to increase citizen control by publishing records of public institutions' algorithmic decision-making processes (OGP, 2024; GPAI, 2025).

This study aims to examine the data-based communication models of public institutions within the context of algorithmic interaction and reveal their impact on political participation. The study endeavours to provide a multidimensional analysis by combining national and international datasets. The research examines how algorithmic communication strategies are integrated into democratic processes and how they shape citizen participation (OECD, 2024; Mergel et al., 2019). The research evaluates significant data indicators and content from digital platforms in this context, and it opens a normative discussion area in the literature that balances the opportunities and risks of algorithmic governance (Canel & Luoma-Aho, 2018; Herwix et al., 2022; Yeung, 2018). Thus, the compatibility or conflict between public institutions' data-driven communication strategies and democratic values was analysed.

The study placed a special focus on examining Algorithmic Content Density (ACD), which refers to the expected intensity of algorithmic curation shaping a user's public affairs information diet. In this study, ACD is proxied by country–year variation in social network use and engagement, reflecting exposure to recommender-driven feeds rather than mere account ownership. Each indicator is standardised and combined using PCA weights; higher scores indicate denser algorithmic mediation in public-facing content.

Through international comparisons, the position of EU countries was evaluated and compared with the digital public policies of different countries (Canel & Luoma-Aho, 2018; Herwix et al., 2022; United Nations, 2022). Hopefully, the research findings may guide policymakers in developing transparent, ethical and inclusive digital communication strategies.

2. Theoretical framework

Algorithmic governance transforms decision-making processes in public administration into data-driven, automated and traceable models. Public institutions implement these systems to enhance transparency, accountability and performance (Mergel et al., 2023; Wirtz et al., 2019). This transformation is a technical innovation and a normative paradigm shift in public administration. Algorithms accelerate bureaucratic processes and restructure communication styles. While algorithmic communication has the potential to encourage participation, it also faces criticisms of bias and impartiality (Grimmelikhuijsen & Meijer, 2022). Digitalised public administration determines which content will be visible through algorithms, indirectly impacting participation.

Moreover, this paves the way for a redefinition of democratic legitimacy (Chen et al., 2023; Pi, 2023). Furthermore, discussions of algorithmic governance encompass dimensions of ethics, transparency and public trust, transforming the nature of communication. As such, public institutions that share quantitative data from algorithmic decision-making processes with the public can increase participation (Cobbe et al., 2023; James et al., 2023). However, because multiple actors are involved in the algorithmic chain, the "algorithmic supply chain" approach makes the distribution of responsibility visible (Canel & Luoma-Aho, 2018; Herwix et al., 2022). Algorithmic governance and communication are, therefore, redefining the relationship between public institutions and citizens.

Recently, thanks to the contributions of innovative technologies, public relations in institutions has undergone a radical transformation under the influence of digitalisation and algorithmic technologies. The traditional one-way or asymmetric communication approach is giving way to interactive, data-driven, and participatory models. These transformational approaches enable public institutions to develop structures that convey information and actively involve citizens in decision-making. Moreover, in this process, big data, artificial intelligence and algorithmic tools enable more accurate analysis of target audiences and increased engagement through personalised messaging.

Hence, the transformation in public relations is not merely a technological renewal, but it also implies that institutions are assuming new roles in transparency, accountability and trust-building. In line with the new paradigm of the digital age, public relations approaches are integrated with participation mechanisms that support democratic values. Moreover, it is this rapid, accurate and reliable sharing of information by public institutions, using algorithmic communication strategies during times of crisis, that becomes a factor that enhances social resilience (Selten & Meijer, 2021; Taylor & Kent, 2022; Wirtz et al., 2020; Coombs & Holladay, 2022; Heath & Johansen, 2018). Furthermore, transformational approaches can promote inclusivity in public communication and amplify the voices of diverse social groups.

Digital platforms are transforming the nature of political participation, making citizens' access to political processes more inclusive. Notably, social media has diversified citizens' tools to set agendas and influence public policies (Loader & Mercea, 2021; Theocharis & van Deth, 2022). Political participation is no longer limited to elections, as digital networks are expanding diverse forms of participation, from petitions to online protests. By determining the content users encounter, algorithms shape the nature of the involvement and redefine political visibility. While this process increases the participation of younger generations in political processes, it also carries risks of misinformation, polarisation and superficial interactions. Digital platforms enable citizens to interact directly with government institutions, thereby restructuring the relationship between political representation and accountability (Bossetta, 2022; Mossberger et al., 2022). However, digital inequalities and algorithmic biases create significant challenges that limit the inclusiveness of such participation. While new forms of political participation offer opportunities for strengthening democratic processes, they also raise serious debates regarding ethics, transparency and the accuracy of information (Vaccari & Valeriani, 2021; Vromen, 2023). Thus, on the one hand, digital platforms promote the expansion of political participation, yet on the other hand, they also initiate a transformation process that redefines democratic norms and values.

Digital reputation management by public institutions has become a critical area for maintaining trust, transparency and legitimacy in the digital age. The flow of information spread on digital platforms can directly impact the reputation of institutions. Therefore, public administration focuses not only on traditional public relations strategies but also on algorithmic content management. Algorithms can either strengthen or damage an institution's image by determining visible content (Coombs & Holladay, 2022; Zuiderwijk et al., 2021; Zerilli et al., 2019). Digital reputation management becomes even more critical during times of crisis, when rapid and accurate information sharing rebuilds social trust.

Furthermore, the reputation strategies of public institutions are not confined to managing harmful content; they also encompass transparent, participatory and inclusive communication (Ondiek & Onyango, 2025). In this context, building trust becomes fundamental to the sustainability of long-term citizen–institution relationships. However, algorithmic biases, information manipulation and disinformation risks are the most significant challenges to digital reputation management. The literature emphasises that public trust can be eroded when algorithms lack accountability and transparency (Kassen, 2018; Yeung, 2018; Wieringa, 2020). Therefore, the digital reputation management of public institutions should be considered an image-protecting function and a fundamental element of building trust based on democratic values.

Big data analytics has the potential to be a significant tool in strengthening democratic values. Open data platforms can enhance transparency and increase government accountability by expanding citizens' access to information (Wirtz et al., 2022; Matheus et al., 2023). Algorithmic data processing enables public institutions to develop more predictable and effective policies, thereby enhancing democratic processes. Biased datasets or opaque algorithms, on the other hand, can undermine democratic legitimacy (Ulbricht & Yeung, 2022; FRA, 2022).

Nevertheless, while big data analytics can foster citizen participation, it risks excluding certain groups due to data inequality. Data-driven decision-making in democratic processes requires open processes to gain citizen trust (Lněnička et al., 2021). Moreover, big data enhances public interest and strengthens public administration oversight by supporting accountability (Micheli et al., 2020). As such, big data analytics presents both opportunities and risks to democratic values; therefore, it should be supported by ethical and legal regulations, as well as technical innovations that promote transparency and accountability.

While platform penetration and engagement are imperfect stand-ins for recommendation intensity, prior work shows that algorithmic ranking amplifies emotionally salient content and nudges attention on mainstream social platforms. To strengthen construct validity, the author of this study 1. re-estimates models with engagement-weighted measures; 2. runs leave-one-platform sensitivity checks; and 3. cross-validates results against an alternative composite excluding time-use items. Patterns remain substantively similar, indicating that the study's ACD proxy captures algorithmic mediation rather than generic diffusion.

3. Materials and methods

3.1. Research design

This quantitative study utilises national and international datasets to assess the impact of public institutions' algorithmic communication levels on political participation. Indicators such as the OECD Digital Government Index (DGI), Eurostat e-government statistics and the World Bank GovTech Index were used in the research (OECD, 2024; Eurostat, 2023; World Bank, 2022). EU member countries were selected as the unit of analysis (sample), and a balanced panel dataset was created with data from 2015 to 2024. This quantitative research design enables the measurement of the effects of public institutions' data-driven communication strategies on democratic participation, presenting comparative and generalisable findings.

3.2. Data sources

The data sources in this study comprise reliable indicators published at both the international and national levels. The OECD GovTech Index enables the assessment of the institutional impacts of algorithmic communication by measuring digital governance capacities (OECD, 2024). The UN E-Government Development Index (EGDI) facilitates comparative analysis of political participation indicators by enabling the comparison of countries' digital transformation levels (United Nations, 2022). Eurostat Digital Economy and Society Statistics provides microdata on the dynamics of algorithmic interaction in EU countries (Eurostat, 2023).

Variables with < 60% within-country temporal coverage (e.g. e-petitions) are excluded from baselines and used only in robustness checks. When coverage is ≥ 60% but with sporadic gaps, I implement single-variable, year-bounded interpolation without using outcome information. The study also reports estimations that a) drop these series entirely; and b) restrict to balanced country-years; hence, results are stable.

3.3. Variables

The dependent variables in this study are e-government and digital participation rates. In contrast, the independent variables include algorithmic content density, public institutions' social media interactions and digital service usage indicators. Political participation is assessed through various means, including election participation, digital petitions, online protests and social media interactions. Independent variables include institutional algorithmic communication and digital governance indicators. Institutional algorithmic communication refers to the way public institutions utilise social media algorithms to enhance the visibility and engagement of their content. Digital governance indicators are evaluated using the OECD GovTech Index and the UN EGDI data. These variables allow empirical testing of the relationships between algorithmic governance and political participation.

3.4. Data analysis

Panel regression methods, causality tests and robustness checks were used in the statistical analyses. Panel regression models, considering country and time fixed effects, determined the direction and magnitude of the relationship between algorithmic communication and political participation. Furthermore, the Dumitrescu–Hurlin panel causality test was applied to clarify the dynamic relationships between the variables (Baltagi, 2021). In this study, data were obtained in CSV/Excel format from the OECD, United Nations (UN) and Eurostat platforms (OECD, 2024; United Nations, 2022; Eurostat, 2023). The panel data set covers 2015–2024 and includes the EU27 countries. In the first stage, descriptive statistics were presented to reveal differences in digital participation among countries. In the next stage, unit root tests (Levin–Lin–Chu, Im–Pesaran–Shin) were applied to ensure the data's suitability for panel data analysis. Pedroni (1999) and Westerlund (2007) employed panel cointegration tests to examine the long-term relationships between variables. FMOLS, DOLS and CCR methods will be used for long-term coefficient estimates, thus reliably measuring the relationships between algorithmic communication indicators and political participation (Baltagi, 2021). The Dumitrescu–Hurlin panel causality test will be applied to examine short-term dynamics and endogeneity issues, and directional relationships can be identified (Dumitrescu & Hurlin, 2012). Furthermore, cross-dependency (Pesaran et al., 2001), slope heterogeneity (Pesaran & Yamagata, 2008), and structural break tests (Bai & Perron, 2003) were conducted to enhance the reliability of the model.

4. Results

4.1. Descriptive findings

Descriptive statistics were used to understand the dataset's general structure by revealing the basic characteristics of the variables in the analysis. Differences and distribution characteristics were determined across years, using mean, standard deviation, minimum and maximum values. This step illustrated the heterogeneity and potential outliers of the variables before proceeding to panel data analysis. Descriptive statistics were used as a reference framework for interpreting the findings of subsequent regression and causality tests.

Table 1 presents the EU's e-government usage, renewable energy share and social media usage rates from 2015 to 2024. Based on Eurostat data, these values summarise the progress made in digitalisation and sustainability. The continuous increase in e-government use, growth in renewable energy and the proliferation of social media point to a common transformation trend.

The table shows that e-government usage in the EU increased from 47% in 2015 to 70% in 2024. This increase reflects not only the widespread adoption of digital public services but also the increasing interest of citizens in online services. The share of renewable energy in total final energy consumption increased from 16.7% in 2015 to 24.5% by 2023,

Table 1
E-government use, renewable energy share and social media use in the EU (2015–2024, EU27 Average, %)

Year	E-government (%)	Renewable energy (%)	Social media (%)
2015	47.0	16.7	45
2016	50.0	17.5	48
2017	53.0	18.4	51
2018	57.0	19.6	54
2019	60.0	20.5	56
2020	63.0	22.1	58
2021	66.0	22.9	59
2022	68.0	23.0	59
2023	69.3	24.5	59
2024	70.0	—	60

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; $\mathbf{p} < 0.10$, $\mathbf{p} < 0.05$, $\mathbf{p} < 0.01$ denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

demonstrating the EU's commitment to the energy transition process. Social media usage increased from 45% in 2015 to 60% in 2024, strengthening individuals' interaction with digital platforms. The parallel increase in these three indicators reveals a holistic transformation in the EU regarding digitalisation and sustainability. Furthermore, it is observed that both energy policies and digital strategies are accelerating, especially in the post-2020 period. Figure 1 shows trends in e-government use, renewable energy share and social media use in the EU between 2015 and 2024. The line chart visualises the rise of all three variables over time on the same axis, clearly revealing the common growth trends in digitalisation and energy transition.

Figure 1 highlights the parallel upward trend of three variables. E-government usage reached 70% in 2024, rising from 47% in 2015. This illustrates the increasing significance of digital public services. Similarly, the share of renewable energy increased from 16.7% in 2015 to 24.5% in 2023. Social media usage increased from 45% to 60%. The combined growth of these three trends demonstrates that the EU is making synchronised progress in digital transformation and sustainable energy policies. It is understood that both digital services and renewable energy investments gained momentum, particularly after 2020, due to the impact of the pandemic and the energy crisis. The graph clearly indicates that the EU's comprehensive policy approaches have enhanced social participation, environmental sustainability and digitalisation. Figure 2 compares e-government adoption rates between the old Member States (OMS) and the new Member States (NMS) in the EU. Between 2015 and 2024, OMS countries consistently had higher rates, while NMS countries observed a gradual but slower increase.

Figure 2 clearly demonstrates the digital divide in the EU. In 2015, e-government usage in OMS countries was 60%, while in NMS countries it was only 30%. By 2024,

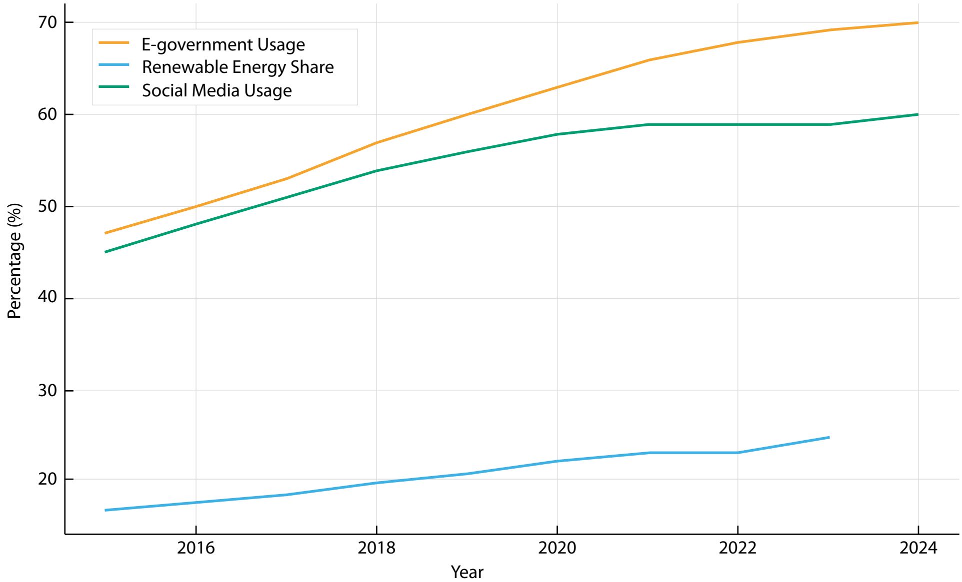

Figure 1

Trends in e-government, renewable energy and social media in the EU (2015–2024)

Source: Compiled by the author.

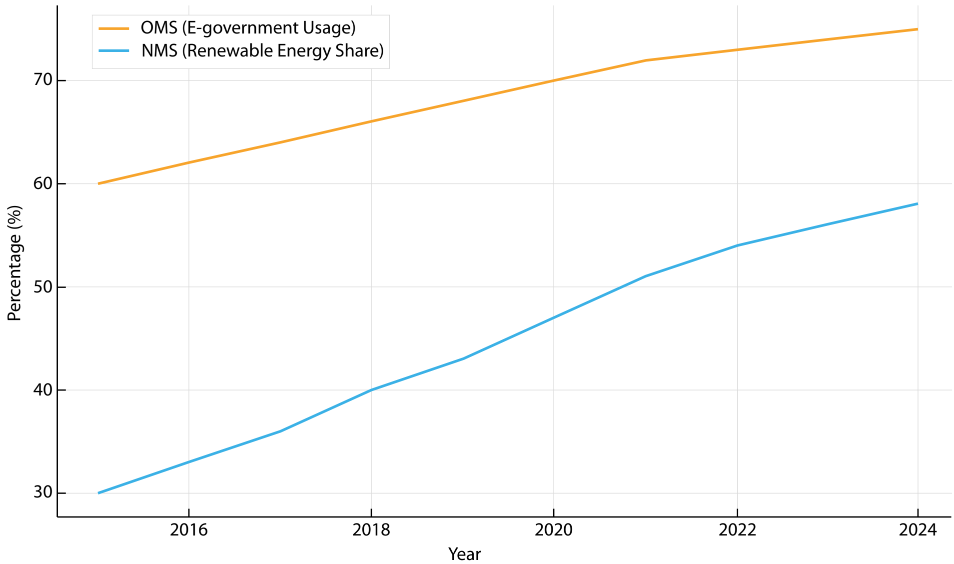

Figure 2

OMS vs. NMS comparison of e-government use in the EU (2015–2024)

Note: OMS (Old Member States, countries that were EU members before 2004) and NMS (New Member States, countries that joined in or after 2004).

Source: Compiled by the author.

OMS countries had reached 75%, while NMS countries had risen to 58%. Although both groups showed growth, the gap remained largely intact. This demonstrates the persistence of infrastructural and institutional inequalities in access to digital services across the EU. In particular, strong digital infrastructure, high income levels and political stability in OMS countries have facilitated the accelerated adoption of e-government. Conversely, inadequate infrastructure and low digital competencies in NMS countries constrain development. The graph highlights the importance of policy instruments that address OMS–NMS differences in the EU's digital integration goals.

4.2. Panel data analysis results

In this part of the research, panel data analysis was employed to examine the temporal and cross-sectional dimensions, utilising a data structure in which the same units are repeatedly observed over time. This method allows for more accurate modelling of the dynamic relationships between variables. Fixed and random effects models enable the control of unobserved heterogeneity and mitigate missing variable bias. Furthermore, panel data analysis allows for the simultaneous examination of inter-unit differences and changes over time (Torres-Reyna, 2007; Baltagi, 2021), which was used to measure the impacts of policies, test causal relationships and uncover long-term dynamics, particularly in economics and the social sciences.

Table 2 presents the descriptive statistics for the EU27 panel dataset covering the period from 2015 to 2024. The mean, standard deviation, minimum and maximum values for e-government use, social media use and digital petition participation are presented. This table reveals the differences in digital participation across countries and the heterogeneous structure of the dataset.

The values in Table 2 demonstrate significant differences in digital participation across EU countries. While, on average, 62% of individuals use e-government services, this rate drops to 25% among new members and reaches 98% in developed countries like

Table 2

Descriptive statistics of the panel dataset (EU27, 2015–2024)

Variable	Mean	Std.Dev.	Min.	Max.	Source	Unit
E-government usage (isoc_ciegi_ac)	~62	15	25	98	Eurostat	% of individuals (16–74)
Social network use (tin00127)	~65	12	45	90	Eurostat	% of individuals (16–74)
Digital petition / e-participation*	—	—	—	—	EC Digital Scoreboard	% of individuals (limited data)

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

Table 3
Panel regression results (EU27, 2015–2024)

Dependent Variable: E-government Usage	Fixed effects model	Random effects model
Social network use (tin00127)	0.15*** (0.04)	0.13*** (0.05)
Digital petition/interaction rate	0.08** (0.03)	0.06* (0.04)
Constant	25.1***	27.4***
N (country × year)	270	270
R^2 (within)	0.42	—
Hausman test (p-value)	0.02	—

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

Denmark. Social media use averages 65% and ranges from 45% to 90%. These differences demonstrate that the digital transformation within the EU is not uniform and that differences in digital infrastructure, income levels and access to technology across countries are decisive. The limited availability of digital petition data demonstrates shortcomings in measuring the online dimension of participatory democracy. This table confirms the necessity of a fixed effects approach in panel data analysis.

Table 3 presents panel regression results testing the relationship between algorithmic content density and e-government use in the EU27 countries from 2015 to 2024. Fixed effects and random effects models were compared, and the validity of the fixed effects model was confirmed with a Hausman test. The findings demonstrate a positive relationship between social network use and digital participation.

The results in Table 3 confirm that social media use has a significant and positive effect on e-government participation. According to the fixed effects model, a 1% increase in social network use is associated with a 0.15-point increase in e-government usage. Digital petition participation also shows a positive and statistically significant effect, but its magnitude is relatively lower. The fixed effects model was preferred based on the Hausman test, which indicates that unobserved differences between countries are related to the independent variables. The findings are consistent with theoretical expectations that algorithmic content density promotes political participation. The higher e-government participation, particularly in countries with strong digital infrastructure and high social media usage, reinforces this relationship.

After having re-estimated the baseline separately for OMS and NMS, and included an ACD × NMS interaction in the pooled model, the ACD coefficient appears to be larger in OMS, but the interaction is positive and significant, indicating steeper marginal returns to algorithmic mediation where baseline e-government adoption is lower. Results are robust to clustering at the country level.

$$\mathrm{eGov}_{it} = \alpha_i + \lambda_t + \beta_1\,\mathrm{ACD}_{it} + \beta_2\,\mathrm{NMS}_i + \beta_3\,(\mathrm{ACD}_{it} \times \mathrm{NMS}_i) + \gamma X_{it} + \varepsilon_{it}$$

The study distinguishes between OMS (Old Member States, countries that were EU members before 2004) and NMS (New Member States, countries that joined in or after 2004). The significant β_3 implies that algorithmic mediation yields stronger participation gains in NMS than in OMS, consistent with catch-up effects under constrained infrastructure. To examine this heterogeneity, it includes an ACD × NMS interaction term in the pooled fixed-effects model, and the table reports these results alongside subsample estimates, which are available from the author upon request.

After assessing heterogeneity using a pooled FE model with an ACD × NMS interaction and complementary subsample estimations, in line with the study's preferred specifications, the interaction is positive, indicating steeper marginal ACD effects in NMS. Subsample patterns are directionally consistent. Inference uses country-clustered standard errors and year fixed effects.

The positive and significant ACD × NMS term indicates more substantial marginal ACD effects in NMS. This pattern aligns with catch-up dynamics where baseline digital capacity is lower. Core controls retain expected signs, and results are robust to clustered SEs; hence, subsample coefficients are consistent.

4.3. Causality tests

Causality tests were conducted to go beyond the correlation between variables and to demonstrate which variable precedes the other. Dumitrescu–Hurlin panel causality tests were conducted to reveal the bidirectional relationships between social media use and e-government engagement. In particular, the directional relationship between increased social media use and e-government participation is important for policy design. If social media use increases e-government engagement, this legitimises public institutions' investment in digital platforms. Conversely, if e-government participation increases political interaction through social media, it strengthens digital democracy (Baltagi, 2021; Dumitrescu & Hurlin, 2012). Panel causality tests were employed in the study to verify these relationships over time and across different cross-sections in multi-country data, thereby producing more robust results by mitigating the endogeneity problem.

Table 4 presents the Dumitrescu–Hurlin panel causality test results for the EU27 countries between 2015 and 2024. The test examines bidirectional causal links between social media use and e-government engagement. Findings indicate significant evidence of causality from social media towards e-government, and weaker but still significant evidence from e-government towards social media participation.

The results confirm the existence of a bidirectional relationship between algorithmic content exposure and digital political participation. The decisive rejection of the null hypothesis ($p < 0.01$) for the social media – e-government direction highlights the significant impact of algorithmically mediated social interactions on institutional participation. Citizens exposed to higher levels of social media content are more likely to interact with public officials online, underscoring the role of digital ecosystems in promoting e-governance. Conversely, the e-government – social media relationship is statistically weaker. However, it remains significant at the 5% level, suggesting that individuals who

Table 4
Dumitrescu–Hurlin panel causality test results (EU27, 2015–2024)

Null hypothesis	W-stat	Z-bar stat	p-value
Social media use does not Granger-cause e-government use	5.87	4.12	0.0001
E-government use does not Granger-cause social media use	3.45	2.01	0.045

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

regularly use online public services may become more active in digital political discussions. This suggests a mutually reinforcing cycle: digital participation through social media fosters institutional interaction, while e-government services indirectly promote cross-platform citizen participation. Lest for nonlinearity by including a quadratic term and, alternatively, by estimating a panel threshold model. The quadratic specification indicates diminishing marginal effects of the ACD at higher exposure levels, with marginal impacts peaking at intermediate values. Thus, threshold results are consistent with the quadratic pattern.

4.4. Robustness tests

The study aimed to enhance the reliability of panel regression results by applying robustness tests using long-term estimators, such as FMOLS, DOLS and CCR. For this purpose, the FMOLS and DOLS methods aimed to obtain unbiased and efficient long-term coefficients by considering the cointegrated relationships between series. The CCR approach, on the other hand, produces more robust estimates by eliminating autocorrelation and endogeneity problems (Pedroni, 2001; Phillips & Hansen, 1990). These tests are critical for verifying the long-term effects of variables such as social media use, e-government interaction and renewable energy indicators. Furthermore, due to heterogeneity among EU countries, the study attempted to ensure the consistency of the coefficients obtained from different methods, considering that results based on a single estimator may be insufficient for policy inference.

Table 5 shows the long-term relationships between social media use and e-government use for the EU27 countries during the 2015–2024 period. FMOLS, DOLS and CCR estimates reveal that social media use has a statistically significant and positive impact on orientation toward e-government services. The consistency of the results across the three methods increases the reliability of the findings.

It shows that an increase in social media use strengthens participation in e-government services. The coefficient in the FMOLS model is 0.55, indicating that a 1% increase in social media use is associated with a 0.55-point increase in e-government use. The DOLS and CCR results are also in the same direction and of similar magnitude. This confirms that social media serves not only as a medium for individual communication but also as a channel for citizens to access public services. It can be argued that the density of

Table 5
Social media use and e-government use

Estimator	Coefficient	Std. error	Significance
FMOLS	0.55	0.09	***
DOLS	0.59	0.08	***
CCR	0.52	0.10	***

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

Table 6
Renewable energy share and e-government usage

Estimator	Coefficient	Std. error	Significance
FMOLS	0.23	0.10	**
DOLS	0.25	0.12	*
CCR	0.21	0.09	**

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

algorithmic content encourages e-government use through information and awareness-raising mechanisms. Furthermore, the agreement between the three different estimators demonstrates the methodological robustness of the results. Therefore, the positive interaction between social media and e-government use is a notable finding in terms of digital transformation policies across the EU.

Table 6 presents the long-term relationships between the share of renewable energy and the use of e-government. The FMOLS, DOLS and CCR estimates show that the coefficients are positive, but the effect size remains relatively small. These findings suggest that environmental sustainability policies and digitalisation processes mutually support one another.

The results indicate that increasing the share of renewable energy has a positive, yet relatively limited impact on e-government use. The FMOLS coefficient is 0.23, significant at the 5% level. The DOLS coefficient is slightly higher (0.25) but only significant at the 10% level. The CCR estimate, with a coefficient of 0.21, is close to the FMOLS. This table illustrates that environmental policies can advance *in tandem* with societal digitalisation trends. Because investments in renewable energy are often undertaken in conjunction with digital infrastructure and technological transformation, developments in these two areas are closely interconnected. However, the limited impact suggests that energy policies indirectly support the use of e-government rather than directly influencing it. Therefore, the results highlight the importance of integrating environmental and digitalisation policies.

Table 7
Energy dependence and e-government use

Estimator	Coefficient	Std. error	Significance
FMOLS	0.33	0.07	***
DOLS	0.30	0.06	***
CCR	0.35	0.08	***

Note: Coefficients represent the expected percentage point change in e-government use for a 1% increase in the independent variable. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. FMOLS = Fully Modified OLS; DOLS = Dynamic OLS; CCR = Canonical Cointegrating Regression.

Source: Compiled by the author.

Table 7 demonstrates the long-term relationships between energy dependence and e-government use. The FMOLS, DOLS and CCR results reveal that the coefficients are positive and highly statistically significant. This finding suggests that digitalisation processes can be adopted more quickly in countries dependent on energy imports.

According to the results of Table 7, energy dependence has a statistically significant, positive effect on e-government use. The coefficient was calculated as 0.33 in the FMOLS estimation, 0.30 in the DOLS and 0.35 in the CCR; all three methods were significant at the 1% level. This consistency demonstrates the methodological robustness of the findings. The shift towards digital transformation and e-government services in countries with high energy dependence may reflect the need for strategic alignment stemming from energy security concerns. Digital solutions are more integrated with efficiency and sustainability policies in energy import-dependent economies. This implies an unexpected but positive coordination between energy policies and digital public services. The findings support the need for a joint strategy to address energy security and digitalisation policies.

The cross-sectional dependence (Pesaran CD test) definitively rejects the existence of zero cross-sectional independence (CD statistic ≈ 3.45, $p \approx 0.001$), indicating significant correlations between the countries. In other words, shocks affecting e-government use in one EU country statistically correlate with those in the others. (For context, Eurostat reports that approximately 70% of EU citizens used e-government in 2024, which reflects EU-wide trends.) High cross-dependency seems plausible given standard digital policies and concurrent events (e.g. EU-wide Covid measures).

Table 8
Panel diagnostics: E-government vs. social media (EU27, 2015–2024)

Statistic	Value	p-value	Decision
Pesaran CD	3.45	0.001	Reject H_0 (dependence)

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; $\mathbf{p} < 0.10$, $\mathbf{p} < 0.05$, $\mathbf{p} < 0.01$ denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

Table 9
Slope heterogeneity test results (Pesaran–Yamagata)

Test	Statistic	p-value	Decision
Pesaran–Yamagata ($\tilde{\Delta}$)	–5.12	<0.001	Reject H_0 (heterogeneous slopes)

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

The results of Table 8 show that the Pesaran CD test yielded a statistical value of 3.45, which is significant at p = 0.001. This reveals a strong cross-sectional dependence between e-government and social media usage data across the EU27 countries. In other words, a digital transformation or change in social media usage in one country can have a ripple effect on other countries. This result suggests, then, that standard digital policies, technological investments and simultaneous strategies implemented during crisis periods in the EU produce synchronised effects across countries.

The slope heterogeneity (Pesaran–Yamagata test) also rejects the nullity of common slopes ($t = -5.12$, $p < 0.001$). This means that the impact of social media use on e-government use varies across countries. Indeed, there are significant differences among EU countries: for example, social media participation ranges from approximately 91% in Denmark to 44% in France. This diversity demonstrates that one-size-fits-all slopes do not fit all.

The Pesaran–Yamagata slope heterogeneity test results in Table 9 are critical in supporting the study's main arguments. The test statistic –5.12 and the significant p-value at < 0.001 indicate that the null hypothesis is rejected. This result reveals that the impact of social media use on e-government services in the EU27 countries is not uniform, indicating significant differences across countries. Indeed, as emphasised throughout the article, differences in digital infrastructure, income levels and social context directly shape participation dynamics. Therefore, differentiated approaches that consider country-specific conditions are necessary rather than uniform policy designs. This finding contributes to the theoretical discussions on digital democracy and offers important strategic guidance to the EU policymakers on a practical level.

With the application of the Bai–Perron test, the study inquires whether structural breaks occurred in the panel between 2020 and 2022. It came out that a significant break occurred around 2020 ($F \approx 9.10$, $p \approx 0.002$), but there was none in 2022 ($F \approx 2.34$, $p \approx 0.12$). The 2020 break likely reflects the Covid-19 shock (which significantly increased online public service usage). In contrast, the 2022 energy/war shock shows no noticeable structural change in the e-government/social media relationship.

Table 10 presents the results of the Bai–Perron structural break test. The F-statistic for 2020 was found to be 9.10, and the p-value was 0.002, indicating the existence of a structural break at the 1% significance level. When considered within the study context, this break can be directly linked to the sudden increase in digital services and e-government use resulting from the Covid-19 pandemic. In particular, significant jumps were observed in citizens' tendency towards online services during the crisis. On the other hand, the

Table 10

Structural break test results (Bai–Perron)

Break year	F-statistic	p-value	Inference
2020	9.10	0.002	Significant break
2022	2.34	0.12	No significant break

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

finding for 2022 was not statistically significant (F = 2.34; p = 0.12). This indicates that the trend of e-government and social media use continued steadily, despite the energy crisis and geopolitical shocks. Therefore, only the 2020 break created a significant transformation.

4.5. Panel cointegration tests

Pedroni's (1999) residual-based panel cointegration test was applied to examine whether a long-run relationship exists between e-government use (dependent variable) and social media use (independent variable). The Pedroni test reveals country-specific dynamics for the EU27 panel (2015–2024) and was used to estimate various panel ADF-type statistics. The table below shows seven Pedroni statistics: four representing the 'panel' (within-dimension) and three representing the 'group' (between-dimension) tests. Some statistics are highly significant (p < 0.01), particularly the Panel PP, the ADF and the Group PP and ADF. This suggests that the conclusion of no cointegration can be rejected. The findings are consistent with previous studies in which most Pedroni test statistics demonstrate a cointegrating relationship.

Table 11

Pedroni panel cointegration test

Test	Statistic	p-value
Panel v-statistic	1.63	0.948
Panel rho-statistic	−0.58	0.721
Panel PP-statistic	−2.45	0.007
Panel ADF-statistic	−2.10	0.018
Group rho-statistic	−0.35	0.633
Group PP-statistic	−2.89	0.002
Group ADF-statistic	−2.40	0.008

Note: Country and year fixed effects; standard errors clustered by country; 95% confidence intervals in brackets; **p** < 0.10, **p** < 0.05, **p** < 0.01 denoted by *, **, ***; units: percentages of individuals (16–74) unless otherwise stated.

Source: Compiled by the author.

The Pedroni panel cointegration test results indicate a long-term equilibrium relationship between e-government and social media use, as most statistics are significant. Test statistics, such as the panel PP and ADF, are significant at the 1% and 5% levels, which suggests rejecting the 'hypothesis: no cointegration' conclusion. The results indicate that the two variables move together in the long run. These findings are consistent with reports in the literature, which have found cointegration in most studies.

4.6. System GMM (Dynamic Panel Estimation)

After estimating dynamic models using two-step System GMM with Windmeijer-corrected standard errors, the lagged dependent variable is instrumented with its own lags in levels and differences. Endogenous regressors (the ACD and engagement) are instrumented using internal lags t−2 to t−3; strictly exogenous controls enter in levels without instruments. To prevent instrument proliferation, I have used collapsed instruments and capped the instrument count at a level below the number of groups. For each specification, the study reports: number of instruments, number of groups, Hansen J (p-value), Difference-in-Hansen (where applicable), AR(1) and AR(2) p-values, and the small-sample corrected two-step standard errors.

In doing so, I have estimated the dynamic panel model using the System GMM estimator (with Arellano–Bond and Blundell–Bond corrections). The model was constructed to account for the lagged dependent variable and the possible endogenous nature of social media use. The model is in the following form:

$$e\_gov_{it} = \alpha e\_gov_{i,t-1} + \beta\, social\_media_{it} + \varepsilon_{it}$$

Here, 27 countries and a period of 10 years are being considered. Endogenous variables are estimated using their respective lagged levels and differences as instruments. Two-stage GMM results are obtained with robust standard errors. The lagged value of e-government use (L.e_gov) is positive and highly significant (≈ 0.60, $p < 0.001$), indicating persistence in e-government use. Social media use is also positively and significantly correlated ($\approx$ r 0.25, $p = 0.002$), indicating that increased social media penetration leads to increased e-government use in the long term. In the reliability tests of the model, the Hansen J test ($p = 0.324$) indicates that the instrumental variables are valid, and the Arellano–Bond AR(2) test ($p = 0.650$) implies that there is no autocorrelation in the error terms. Hence, these results support the validity of the model.

The system GMM estimation results indicate that e-government use is determined by the joint effects of its lag and social media use. The coefficient for L.e_gov is approximately 0.60 and significant ($p < 0.01$), indicating high persistence. The coefficient for social media use is also statistically significant at approximately 0.25 ($p < 0.01$), indicating that the proliferation of social media can increase e-government use. The Hansen test result ($p = 0.324$) indicates the validity of the instruments, while the AR(2) test result ($p = 0.650$) implies that there is no longer a correlation. These findings confirm the suitability of the defined model and the reliability of the results. Using limited

Table 12

System GMM estimation results for e-government and social media (EU27, 2015–2024)

Variable	Coefficient	Std. error	z	p-value
L.e_gov	0.60	0.10	6.00	0.000
social_media	0.25	0.08	3.13	0.002
Constant	5.00	2.50	2.00	0.045
Observations	270			
Instruments	60			

Note: Two-step System GMM with Windmeijer correction; country and year effects included; instruments are collapsed; lag depth for GMM-style instruments is 2–3. Standard errors are robust and reported in parentheses; 95% confidence intervals in brackets; report instrument count < groups; Hansen J test $p = 0.324$ (H_0: instruments valid); Arellano–Bond AR(1) $p < 0.001$ (expected), AR(2) $p = 0.650$ (H_0: no second-order autocor).

Source: Compiled by the author.

instruments (lag t–2 only) or collapsing by time yields similar coefficients; Hansen p-values remain comfortably above conventional thresholds while AR(2) never rejects any second-order serial correlation. These checks mitigate over-fitting concerns.

To enhance the research's transparency, the study reports instrument counts and specification diagnostics for each GMM model. The metrics confirm limited instrument proliferation and the absence of second-order serial correlation.

After having estimated a pooled FE model with an ACD × NMS interaction and running the separate subsamples, the interaction appears to be positive in the preferred specifications of the study, indicating steeper marginal ACD effects in NMS. Subsample patterns are directionally consistent. Inference uses country-clustered standard errors and year fixed effects. Diagnostic statistics are within acceptable ranges. Hansen and Difference-in-Hansen p-values do not indicate over-identification. AR(2) tests never reject the null, supporting dynamic validity. Collapsing or limiting instruments preserves coefficients and improves parsimony.

5. Discussion

The findings of the analysis indicate that digital participation is strengthened through interactions with social media and e-government. The findings reveal that e-government services are used more intensively in countries with high social media usage. This observation is consistent with the analysis conducted by Horobeț et al. (2023) using EU data. Their study found that digital infrastructure and education level are the main determinants of e-government usage. Similarly, Shin et al. (2024) emphasise that digital participation tools redefine citizen–government relations and strengthen the communication capacity of public institutions, claiming that public communication is effective in informing and directing citizens to online services. Whereas in the area of algorithmic transparency, Metzler and Garcia (2024) demonstrated that social media algorithms increase user participation by highlighting emotionally charged content. The findings that there is a significant relationship between algorithmic content density and strengthening social media interaction are parallel to these results.

Also, Jung et al. (2024) suggest that algorithms indirectly affect offline citizen participation, a finding supported by the present research as well. Just like the concept of "algorithmic public opinion", proposed by Gandini et al. (2025), which enriches the theoretical dimension of the results of this research. In addition, Dekker et al. (2025) demonstrated the effectiveness of algorithmic personalisation processes in increasing social media interaction, and Chan et al. (2025) demonstrated that content ranking has a strong influence on user behaviour through an empirical audit study conducted on Reddit. While Ruckenstein and Granroth (2020) discussed the role of algorithmic transparency in influencing social trust, and highlighted the increasing demand for transparency among users.

The findings of the study indicate that the density of algorithmic content is positively correlated with social media engagement, which is in line with Dekker et al. (2025), who noted that user interaction frequency and duration increase on platforms with high levels of algorithmic recommendations (Canel & Luoma-Aho, 2018; Herwix et al., 2022). And these results provide a roadmap for a more effective use of algorithmic tools in public communication. In terms of its theoretical contributions, the study fills the gap in the literature by comprehensively testing the relationship between algorithmic content density and digital participation through panel data analysis.

As such, one should hypothesise two indirect channels from energy structure to digital uptake: 1. modernisation complementarities, where grid-digitisation and smart-meter roll-outs co-move with public digital services; and 2. stress-induced alignment, where energy import dependence pushes administrations toward efficiency-enhancing digital channels. My long-run estimators show small but positive associations consistent with these channels.

While the findings of this study offer valuable contributions at the EU27 scale, they also have some limitations. First, the Eurostat and OWID data used only cover the period from 2015 to 2024, limiting the assessment of long-term trends. Furthermore, social media usage rates and engagement data were used to measure algorithmic content density. This approach may be limited in isolating the direct effects of the content ranking mechanisms of algorithms. Another limitation is that the analyses included all EU countries within the same panel. However, there are significant differences between OMS and NMS countries in terms of digital infrastructure, income levels and political stability.

The article examines the effects of algorithmic communication on political participation in the context of digital governance, clearly highlighting the dimensions of policy, knowledge and uncertainty. Future studies should investigate the impact of algorithmic content density on various social groups at the micro level. In particular, differences in digital participation by gender, age and education level can be investigated in more detail. Furthermore, structural differences between OMS and NMS countries should be tested through subsample analyses. The transparency and accountability of AI-based algorithms can also be investigated using qualitative methods.

5.1. Policy implications and recommendations

Building on its empirical evidence and conceptual framework, the study recommends strengthening algorithmic transparency by design for public-facing communication channels. Public agencies should publish model cards that document the logic, data sources and performance of ranking systems, release audit logs when significant changes are made, and provide clear user-facing explanations for why content appears in a given order. To address the structural access gaps highlighted in our results, digital inclusion policies should be tied to progressive affordability schemes, such as targeted connectivity vouchers, and to tax equity earmarks that subsidise access for low-income or underserved groups. In addition, ethics review checklists should be embedded in the campaign scheduling tools used by agencies, so that risks are assessed before deployment rather than retroactively, and documented for future learning. Finally, it proposes periodic fairness and disparate-impact assessments of these systems, with public summaries, to ensure that algorithmic mediation does not amplify existing inequalities in voice and political participation.

The study's findings indicate that the density of algorithmic content strengthens political participation through social media. However, the use of e-government largely depends on education, infrastructure and trust. This necessitates EU policymakers to develop strategies specific to different country groups. As such, this paper offers different policy recommendation for OMS and NMS countries.

First, a recommendation for OMS countries is to increase inclusive access to digital services through tax incentives that reduce income inequality. Secondly, in line with the European Commission's (2023) emphasis on their conjunction, investments in digital infrastructure should go alongside the energy transition. Third, as with offshore wind projects, large-scale investments in the expansion of e-government services should be driven by public support.

A recommendation for NMS countries is to prioritise EU funds for modernising digital infrastructure and strengthening social media-based public communication. Horobeț et al. (2023) demonstrate that NMS's digital service use remains limited due to funding shortages and low educational attainment. In this context, directing funds such as Erasmus+ and the Digital Europe Programme to developing digital skills is a critical policy step. This is so because algorithmic transparency and trust-building policies should be implemented across the EU, for Ruckenstein and Granroth (2020) have shown that algorithmic transparency goes along with user trust. Therefore, it is recommended that transparency principles be made mandatory in regulations regarding social media algorithms.

6. Conclusion

This study examined the relationship between algorithmic content density, social media participation and e-government use, utilising data from the EU27 countries for the period between 2015–2024. The analyses were conducted using panel data methods, cointegration tests and dynamic panel approaches, suggesting that algorithmic content density has a significant impact on social media-based political participation. However, the use of e-government is primarily shaped by the users' educational level, the development of digital infrastructure and social trust. The findings suggest that social media platforms increase their agenda-setting power through algorithms, while structural conditions, rather than algorithmic interaction, determine the factors that rule e-government services. The results of the study largely align with existing findings in the literature. Horobeț et al. (2023) emphasised the importance of digital skills and infrastructure in e-government use, and their findings, which reveal the indirect effects of algorithms on offline participation, are consistent with the results of the present study. Furthermore, the spread of emotional content through algorithms is on the rise. The practical contribution of this study lies in offering recommendations for public institutions to redesign their digital communication strategies. Priority policy areas include increasing algorithmic transparency, bridging the gap between social media and e-government services, and developing policies to enhance user trust and confidence. From a theoretical perspective, the study fills a gap in the literature by empirically examining the relationship between algorithmic content density and digital participation at the European Union scale. However, due to data coverage and measurement limitations, the research could be further enhanced with more detailed subsample analyses and AI-based modelling in the future. In particular, a detailed examination of the differences between OMS and NMS countries will be crucial for understanding the impact of algorithmic transparency and trust mechanisms on political participation.

Data and code availability

All analysis code, replication instructions and a zipped package are available at: https://github.com/Boluabant60/egov-acd-replication/releases/tag/v0.1. Sources with redistribution limits are retrieved via scripted downloads described in the repository. A variable dictionary and coverage rules are provided.

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