

EFFICIENCY OF DIGITAL TRANSFORMATION IN THE EU-27: A SEQUENTIAL BI-OBJECTIVE MCDEA BCC, SUPER-EFFICIENCY AND SLACK-BASED MEASURE FRAMEWORK

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Abstract: Digital transformation has become increasingly important for improving public-sector performance and the delivery of electronic government services. Nevertheless, European Union (EU) member states differ substantially in their ability to convert digital access, institutional support, and innovation-related resources into effective digital public-service outcomes. This study evaluates the relative efficiency of digital transformation across the EU-27 using a sequential Data Envelopment Analysis (DEA) framework. Three input indicators—Internet Users, Government Support, and Gross R&D Expenditure—and three output indicators—Online E-Government Services, Satisfaction with eID, and Interaction with Public Administration—are examined. The analytical framework comprises three complementary stages. The Bi-Objective Multiple Criteria Data Envelopment Analysis (MCDEA) BCC Output-Oriented model is first used to estimate relative efficiency and identify frontier-efficient countries. Super-Efficiency analysis is subsequently applied to the frontier-efficient countries to provide additional discrimination, whereas the non-oriented Slack-Based Measure (SBM) model is used to examine input excesses, output shortfalls, and benchmark projections among

the remaining countries. The Bi-Objective MCDEA BCC results identify Hungary and Portugal as frontier-efficient, each with an efficiency score of 1.000. Super-Efficiency analysis produces scores of 0.9999997 for Hungary and 1.009678 for Portugal, providing further differentiation between the two frontier countries. The SBM analysis reveals substantial heterogeneity in non-radial efficiency, with Cyprus recording the lowest SBM score of 0.2117047 within the evaluated EU-27 sample. The slack analysis further demonstrates that relatively inefficient countries exhibit different combinations of unused enabling capacity and output shortfalls. The sequential framework therefore provides complementary evidence on efficiency measurement, frontier discrimination, and inefficiency diagnosis, thereby extending digital-transformation benchmarking beyond reliance on a single efficiency score.

Keywords: Data Envelopment Analysis; Bi-Objective MCDEA; Super-Efficiency; Slack-Based Measure; digital transformation; EU-27

Introduction

Digital transformation has become a central component of economic modernization and public-sector development. Governments increasingly employ digital technologies, electronic identification systems, data-driven platforms, and online service channels to improve accessibility, administrative efficiency, and interaction with citizens. Within the European Union, digitalization of public administration has assumed particular importance because member states are expected to provide increasingly responsive, accessible, and efficient electronic government services while operating under different institutional and resource conditions.

Despite the widespread adoption of digital technologies, substantial differences remain in the extent to which countries convert enabling conditions into observable public-service outcomes. High levels of Internet penetration, government support, and innovation-related investment do not necessarily produce proportionately high levels of online service availability, satisfaction with electronic identification, or citizen interaction with public administration. Consequently, a meaningful assessment of digital transformation requires an analytical framework that evaluates several inputs and outputs simultaneously rather than treating individual indicators in isolation.

Data Envelopment Analysis (DEA) provides an appropriate non-parametric framework for this purpose because it evaluates the relative efficiency of comparable decision-making units (DMUs) in the presence of multiple inputs and outputs without requiring prior specification of a production function. DEA has increasingly been applied to digitalization and electronic government. Inel (2019) employed DEA to assess digital-transformation efficiency, while Yalçın (2021) evaluated digitalization efficiency across EU countries. Georgescu et al. (2022) examined the efficiency of digital transformation among EU member states during the COVID-19 period, and Krejnus et al. (2023) investigated the efficiency of electronic public administration using digitalisation and e-government indicators. Subsequent work has broadened the methodological treatment of digital development through tiered DEA, composite indicators, cluster analysis, and Malmquist productivity measures (Bánhidi & Dobos, 2023; Horváthová & Mokrišová, 2024; Bánhidi & Dobos, 2024).

Although the existing literature demonstrates the usefulness of DEA for cross-country digital benchmarking, reliance on a single efficiency measure may provide incomplete decision-

support information. Conventional DEA-type models can assign the same frontier score to several DMUs, thereby limiting discrimination among efficient observations. In addition, an aggregate efficiency score does not necessarily identify the specific input excesses or output shortfalls associated with inefficient performance. Multiple Criteria Data Envelopment Analysis (MCDEA) has been developed to strengthen discriminatory capability and to address limitations related to flexible weighting and weak differentiation (Ghasemi et al., 2014; Hatami-Marbini & Toloo, 2017; da Silva et al., 2020). Recent research has further extended MCDEA to variable-returns-to-scale settings and incorporated super-efficiency analysis for improved discrimination among frontier units (da Silva et al., 2024).

The present study addresses these limitations through a sequential application of three DEA-based models that perform distinct but complementary analytical functions. The Bi-Objective MCDEA BCC Output-Oriented model provides the primary assessment of relative efficiency and identifies countries located on the estimated frontier. Super-Efficiency analysis is subsequently applied to the frontier-efficient DMUs to obtain additional discrimination among units that share the frontier score. The SBM model is then used as a non-radial diagnostic measure because it explicitly incorporates input and output slacks and therefore permits closer examination of the sources of inefficiency and the associated benchmark projections. The complementary use of efficiency, super-efficiency, and slack-based measures is supported by methodological developments that integrate or jointly interpret these concepts within DEA analysis (Guo et al., 2017; Tran et al., 2019; Xie et al., 2021).

Accordingly, the study makes three contributions. First, it applies a sequential DEA framework that distinguishes relative-efficiency measurement, frontier discrimination, and slack-based inefficiency diagnosis. Second, it provides an empirical assessment of digital-transformation efficiency across the EU-27 using a common input-output structure. Third, it extends the interpretation of DEA results beyond a single efficiency ranking by examining the specific slack profiles and benchmark targets associated with relatively inefficient countries. Consistent with these contributions, the study has three research objectives: to evaluate the relative efficiency of digital transformation across the EU-27 using the Bi-Objective MCDEA BCC Output-Oriented model; to discriminate among the frontier-efficient countries using the Super-Efficiency model; and to identify input slacks, output shortfalls, and model-based improvement targets among relatively inefficient countries using the SBM model.

Research Methodology

Research Design and Analytical Framework

This study adopts a quantitative efficiency-benchmarking design in which the 27-member states of the European Union constitute the DMUs. All countries are evaluated using an identical set of three input and three output indicators, thereby satisfying the homogeneity requirement that underpins comparative DEA applications.

The empirical procedure is organized into three analytically distinct but sequential stages. In the first stage, the Bi-Objective MCDEA BCC Output-Oriented model is estimated for all 27 DMUs to determine relative efficiency and identify the countries located on the estimated efficiency frontier. In the second stage, the Super-Efficiency model is applied exclusively to the frontier-efficient DMUs identified in the first stage. This stage does not constitute a second screening of the full sample; rather, it provides additional discrimination when more than one DMU attains the frontier score. In the third stage, the non-oriented SBM model is employed to

evaluate slack-sensitive efficiency and to derive input excesses, output shortfalls, and projected benchmark values for the relatively inefficient countries.

The sequential design reflects the distinct analytical properties of the three models. The initial MCDEA model provides an overall relative-efficiency assessment with enhanced discriminatory capability, the Super-Efficiency model differentiates frontier observations, and the SBM model provides a non-radial assessment of the specific inefficiency dimensions that are not captured by an aggregate frontier score. The three models are therefore interpreted as complementary components of a single analytical framework rather than as competing approaches expected to generate identical rankings.

Data Source and Decision-Making Units

The empirical dataset covers the 27 EU member states and is based on the indicator structure reported by Krejnus et al. (2023), who compiled comparable measures of digital access, government support, innovation capacity, e-government service availability, electronic identification, and online interaction with public administration. The original manuscript described the dataset as representing the 2022 digital-transformation context. For the revised analysis, the country-level observations were cross-checked against the source table reported by Krejnus et al. (2023) to ensure consistency between the input-output data and the subsequent efficiency calculations.

The use of the term EU-27 is maintained throughout the revised manuscript because the empirical sample consists specifically of the 27-member states of the European Union rather than all geographically European countries. This distinction ensures that the scope of the title, interpretation, and conclusions is consistent with the actual set of DMUs.

Input and Output Variables

The input-output specification represents a simplified transformation process in which digital access, institutional support, and innovation-related capacity are treated as enabling conditions, while observable public-service outcomes are treated as outputs. The selection is consistent with the conceptual structure employed by Krejnus et al. (2023) and with previous DEA studies of digitalisation and electronic government (İnel, 2019; Yalçın, 2021; Georgescu et al., 2022).

Table 1. Definition and Role of Input and Output Variables

Variable	DEA Role	Measurement	Conceptual Interpretation
Internet Users	Input	Percentage	Digital access and participation capacity
DSGI - Government Support	Input	Score	Institutional support for digital skills and development
Gross R&D Expenditure (% of GDP)	Input	GII-derived score	Innovation-related economic capacity
Online E-Government Services	Output	Percentage	Availability of public services through digital channels

Satisfaction with eID	Output	Percentage	User experience with electronic identification
Interaction with Public Administration	Output	Percentage	Realised online interaction between citizens and public administration

Internet Users is treated as an input because widespread connectivity constitutes a basic access condition for the use and delivery of digital public services. Government Support represents the institutional dimension of digital development, particularly the extent to which public authorities support digital skills and digitalisation. Gross R&D Expenditure represents innovation-related capacity. In the source dataset, this indicator is operationalised using the Global Innovation Index (GII)-based score associated with R&D expenditure as a percentage of GDP; consequently, the observed values should be interpreted as index-based scores rather than as literal percentages of national GDP.

The three outputs capture conceptually distinct dimensions of realised digital-government performance. Online E-Government Services represents the availability of services through digital channels, Satisfaction with eID captures user experience with electronic identification, and Interaction with Public Administration reflects realised citizen engagement with public authorities through online channels. Although the three measures are related to digital government, they represent service availability, user experience, and administrative interaction, respectively, thereby reducing conceptual overlap within the output set.

EU-27 Digital-Transformation Dataset

Table 2 below shows the raw data for the EU-27 countries.

Table 2. Input and Output Data for the EU-27

DMU	Country	Internet Users	Government Support	R&D Score	Online Service	eID Satisfaction	Administration Interaction
1	Luxembourg	99	9	20.6	92	67	49
2	Austria	88	5.7	58.8	89	85	67
3	Belgium	92	5.2	63.9	87	72	63
4	France	92.2	5.6	43.2	90	46	56
5	Germany	94	6.2	57.8	87	53	50
6	Netherlands	95.3	6.4	42.1	94	86	86
7	Hungary	89.3	3.1	29.4	90	77	81
8	Czech Republic	86.8	3	36.5	80	44	64
9	Slovakia	90	3.5	16.6	63	75	57
10	Poland	91.5	2.7	25.5	79	77	34
11	Bulgaria	70	3.9	15.5	67	42	24
12	Romania	78	2.8	8.5	50	20	12
13	Sweden	97.3	6.9	64.8	87	75	88
14	Denmark	97.7	5.9	55.7	98	93	92
15	Finland	94.1	6.4	53.9	97	96	88
16	Ireland	92	6.4	22.5	87	45	68
17	Estonia	96.1	7.9	32.9	95	96	75

18	Latvia	89.8	4	12.9	91	86	73
19	Lithuania	97.8	5.3	21.1	85	89	65
20	Slovenia	87	3.5	39.4	79	66	68
21	Spain	93	3.9	25.7	87	83	59
22	Malta	100	6.4	12.3	99	98	58
23	Portugal	88.1	6.6	29.6	95	89	50
24	Croatia	93.2	2.9	22.8	80	60	52
25	Italy	90.8	2.4	28	84	61	31
26	Greece	78.5	1.8	27.4	66	34	66
27	Cyprus	100	3.6	15	56	8	62

Adequacy of the Number of DMUs

The analysis contains 27 DMUs, three inputs, and three outputs. The number of observations is therefore sufficient relative to the dimensionality of the specified DEA structure according to commonly applied DEA adequacy considerations. Maintaining a parsimonious six-variable specification is particularly important because an excessive number of variables relative to the number of DMUs can weaken discriminatory power and increase the proportion of units classified as efficient.

The use of MCDEA provides an additional methodological safeguard because multiple-criteria DEA approaches were developed partly to improve discrimination and address highly flexible weight structures in conventional DEA. Ghasemi et al. (2014), Hatami-Marbini and Toloo (2017), and da Silva et al. (2020) demonstrate the role of MCDEA-type models in strengthening discrimination among DMUs, while da Silva et al. (2024) extends MCDEA to a variable-returns-to-scale environment with super-efficiency analysis.

Bi-Objective MCDEA BCC Output-Oriented Model

The first analytical stage employs the Bi-Objective MCDEA BCC Output-Oriented model. MCDEA extends the conventional DEA framework by incorporating multiple optimisation criteria intended to strengthen the discriminatory capacity of the efficiency assessment. Ghasemi et al. (2014) demonstrated that a bi-objective MCDEA formulation can improve discrimination, while later studies have continued to develop MCDEA models to address weak discrimination and weight dispersion (Hatami-Marbini & Toloo, 2017; da Silva et al., 2020). The BCC specification is retained because the EU-27 countries operate at markedly different economic, institutional, and technological scales. A variable-returns-to-scale perspective is therefore conceptually appropriate for cross-country benchmarking because it does not impose strict proportionality between changes in inputs and outputs. The output orientation is consistent with the substantive objective of the study, which is to evaluate how effectively the observed digital-enabling conditions are converted into higher levels of digital public-service outcomes.

The mathematical formulation used in the original study is reproduced below to preserve consistency with the reported calculations.

$$\text{Min } h = \left(w_2 M + w_3 \sum_{j=1}^n d_j \right) \quad (1)$$

Subject to:

$$\sum_{i=1}^m v_i x_{i_0} = 1, \quad (2)$$

$$\sum_{r=1}^s u_r y_{r_j} - \sum_{i=1}^m v_i x_{i_j} + d_j = 0, j = 1, \dots, n, \quad (3)$$

$$M - d_j \geq 0, j = 1, \dots, n, \quad (4)$$

$$u_r \geq \varepsilon, r = 1, \dots, s, \quad (5)$$

$$v_i \geq \varepsilon, i = 1, \dots, m, \quad (6)$$

$$d_j \geq 0, j = 1, \dots, n, \quad (7)$$

In the formulation, d_0 denotes the deviation associated with the DMU under evaluation, d_j denotes the deviation associated with DMU j , M represents the maximum deviation term, u_r and v_i are the output and input weights, n is the number of DMUs, s is the number of outputs, and m is the number of inputs. A score of 1.000 identifies a DMU located on the estimated frontier under the specified model, whereas a value below 1.000 indicates relative inefficiency within the observed EU-27 comparison set.

Super-Efficiency Model

The second analytical stage applies the Super-Efficiency model to the DMUs identified as frontier-efficient in the first stage. Conventional DEA-type models frequently assign a value of unity to several efficient units and therefore provide limited discrimination within the frontier set. Andersen and Petersen (1993) introduced the super-efficiency concept to address this limitation by excluding the DMU under evaluation from its own reference set and reassessing its position relative to the remaining observations.

In the present study, Super-Efficiency is therefore used as a post-efficiency discrimination procedure rather than as a second screening model for the full sample. The exclusion of Phase-1 inefficient countries from this stage is consistent with the methodological purpose of super-efficiency, namely the differentiation of units that already attain the frontier score. This sequential use is supported by later methodological studies that distinguish conventional efficiency estimation from the ranking of efficient DMUs (Guo et al., 2017; Xie et al., 2021) and by MCDEA research that incorporates super-efficiency within enhanced discrimination frameworks (Hatami-Marbini & Toloo, 2017; da Silva et al., 2024). The mathematical formulation used in the original study is reproduced below.

$$Max, \theta_0 = \sum_{j=1}^m u_j y_{j_0} + u_0 \quad (8)$$

$$\sum_{i=1}^s v_i x_{i_0} = 1, \quad (9)$$

$$\sum_{j=1}^m u_j y_{j_k} - \sum_{i=1}^s v_i x_{i_k} + u_0 \leq 0, k = 1, \dots, n, k \neq 0, \quad (10)$$

$$u_j, v_i \geq 0, \quad (11)$$

In this formulation, θ_0 denotes the Super-Efficiency score of the DMU under evaluation, u_j and v_i denote output and input weights, u_0 is the unrestricted constant associated with the variable-returns-to-scale specification, and x_{ik} and y_{jk} denote the observed input and output quantities for comparator DMU k . By excluding the evaluated frontier DMU from the reference set, the model permits differentiation among units that received identical frontier scores in the first analytical stage.

Slack-Based Measure Model

The third analytical stage employs the non-oriented Slack-Based Measure introduced by Tone (2001). In contrast to radial DEA measures, SBM explicitly incorporates input excesses and output shortfalls into the objective function. This property is important for diagnostic analysis because DMUs with comparable aggregate efficiency scores may exhibit markedly different slack structures and therefore require different improvement priorities.

The non-oriented specification is used because the diagnostic objective of this stage differs from the output-expansion objective of the first stage. Whereas the Bi-Objective MCDEA BCC model evaluates relative performance primarily through an output-oriented frontier perspective, the SBM analysis simultaneously examines inefficiency arising on both sides of the input-output structure. Subsequent methodological developments have continued to emphasise the usefulness of slack-based and super-efficiency measures for identifying sources of inefficiency and improving discriminatory information (Guo et al., 2017; Tran et al., 2019; Tone et al., 2020; Emrouznejad et al., 2025).

The SBM formulation used in the original study is reproduced below.

$$\text{Min } \tau = t - \frac{1}{m} \sum_{i=1}^m \frac{S_i^-}{x_{i0}} \quad (12)$$

$$1 = t + \frac{1}{s} \sum_{r=1}^s \frac{S_r^+}{y_{r0}} \quad (13)$$

$$tx_{i0} = \sum_{j=1}^m \pi_j x_{ij} + S_i^-, i = 1, \dots, m \quad (14)$$

$$ty_{r0} = \sum_{j=1}^n \pi_j y_{rj} - S_r^+, r = 1, \dots, s \quad (15)$$

$$\pi_j \geq 0, S_i^- \geq 0, S_r^+ \geq 0, t \geq 0 \quad (16)$$

Here, S_i^- represents the input slack associated with input i , S_r^+ represents the output slack associated with output r , x_{i0} and y_{r0} are the observed input and output values of the DMU under evaluation, π_j is the intensity variable associated with comparator DMU j , and t is the transformation variable used in the linearised SBM formulation. An SBM score closer to unity indicates stronger non-radial efficiency after accounting for the observed slacks. The optimisation solution also provides benchmark projections that can be interpreted as model-based improvement requirements for relatively inefficient DMUs.

Computational Procedure

The analysis was implemented using LINGO 20.0, as reported in the original manuscript. The computational procedure began with verification of the 27-by-6 input-output dataset. The Bi-Objective MCDEA BCC Output-Oriented model was then estimated for each of the 27 DMUs to obtain the Phase-1 efficiency scores and identify the frontier-efficient countries. The Super-Efficiency model was subsequently applied to the Phase-1 frontier units to provide further discrimination. The remaining countries were evaluated using the non-oriented SBM formulation, from which the efficiency scores, input slacks, output shortfalls, and benchmark projections were obtained.

To strengthen reproducibility, the revised analysis re-evaluated the reported SBM results directly from the published input-output data and the mathematical formulation presented in Equations (12)-(16). After correction of the two transcription errors in the Romania output row, the reported SBM scores were reproduced to numerical precision. The subsequent interpretation therefore distinguishes the overall efficiency scores from the model-specific slack and projection information.

Results and Discussion

Relative Efficiency under the Bi-Objective MCDEA BCC Model

The first analytical stage reveals substantial variation in relative digital-transformation efficiency across the EU-27. Hungary and Portugal each attain a score of 1.000 and are therefore identified as frontier-efficient under the specified Bi-Objective MCDEA BCC model. The remaining 25 countries record scores below unity. Latvia records the highest Phase-1 score among the non-frontier countries at 0.9884256, followed by Finland at 0.9535345, Denmark at 0.9395549, Austria at 0.9352439, and Malta at 0.9347055. At the lower end of the distribution, Cyprus and Romania record Phase-1 efficiency scores of 0.5670464 and 0.5919617, respectively.

These results are interpreted as relative rather than absolute measures of digital performance. A frontier score indicates that, given the selected inputs, outputs, model specification, and comparison set, no observed combination of peer countries dominates the evaluated DMU. It does not imply that the country has achieved universally superior digital transformation across every possible indicator. This qualification is particularly important in cross-country DEA applications because the frontier is sample-dependent and conditional on the variables included in the model.

Super-Efficiency Discrimination of Frontier DMUs

Hungary and Portugal both attain the Phase-1 frontier score of 1.000. Super-Efficiency analysis is therefore used to distinguish their relative positions after exclusion of the evaluated DMU from its own reference set. Portugal records a Super-Efficiency score of 1.009678, while Hungary records 0.9999997. On the basis of the reported model, Portugal consequently receives the higher Super-Efficiency value within the frontier set.

The interpretation of this result is restricted to the analytical design employed in the study. The finding does not establish Portugal as categorically the most digitally advanced country in Europe; rather, it indicates that Portugal occupies the stronger super-efficiency position among the two Phase-1 frontier DMUs under the specified EU-27 input-output structure. The result illustrates the distinct role of the second analytical stage: the initial model establishes frontier membership, whereas Super-Efficiency provides additional discrimination when several countries share the frontier score.

Table 3. Efficiency Results across the Three Analytical Stages

Country	Bi-O MCDEA BCC	Phase-1 Status	Super- Efficiency	SE Rank	SBM
Luxembourg	0.8399558	Inefficient	-	-	0.5256410
Austria	0.9352439	Inefficient	-	-	0.6578764
Belgium	0.8885943	Inefficient	-	-	0.5728475
France	0.9265493	Inefficient	-	-	0.4748444
Germany	0.8568320	Inefficient	-	-	0.4417128
Netherlands	0.9264243	Inefficient	-	-	0.8035673
Hungary	1.0000000	Frontier efficient	0.9999997	2	-
Czech Republic	0.8958898	Inefficient	-	-	0.6764960

Slovakia	0.6928828	Inefficient	-	-	0.7535858
Poland	0.8008978	Inefficient	-	-	1.0000000
Bulgaria	0.8831649	Inefficient	-	-	0.4871282
Romania	0.5919617	Inefficient	-	-	0.3357690
Sweden	0.8188645	Inefficient	-	-	0.6093215
Denmark	0.9395549	Inefficient	-	-	1.0000000
Finland	0.9535345	Inefficient	-	-	1.0000000
Ireland	0.8846527	Inefficient	-	-	0.5394757
Estonia	0.9060490	Inefficient	-	-	1.0000000
Latvia	0.9884256	Inefficient	-	-	1.0000000
Lithuania	0.8387189	Inefficient	-	-	0.7228869
Slovenia	0.8876277	Inefficient	-	-	0.7185742
Spain	0.9022382	Inefficient	-	-	0.7510908
Malta	0.9347055	Inefficient	-	-	1.0000000
Portugal	1.0000000	Frontier efficient	1.0096780	1	-
Croatia	0.8317072	Inefficient	-	-	0.8257416
Italy	0.8488846	Inefficient	-	-	1.0000000
Greece	0.8480765	Inefficient	-	-	1.0000000
Cyprus	0.5670464	Inefficient	-	-	0.2117047

Slack-Based Measure Efficiency

The SBM results provide a different but complementary perspective on relative performance. Several countries that record Phase-1 MCDEA scores below unity obtain an SBM score of 1.000, including Poland, Denmark, Finland, Estonia, Latvia, Malta, Italy, and Greece. This difference does not indicate a computational contradiction. The models employ different optimisation structures and therefore evaluate efficiency from different perspectives. The Bi-Objective MCDEA BCC model emphasises multi-criteria efficiency discrimination, whereas SBM evaluates non-radial efficiency through the explicit treatment of input and output slacks. Among the countries with SBM values below unity, Cyprus records the lowest score at 0.2117047, followed by Romania at 0.3357690, Germany at 0.4417128, France at 0.4748444, and Bulgaria at 0.4871282. These values are interpreted as model-specific relative-efficiency results within the EU-27 comparison set. Accordingly, the finding for Cyprus is stated as the lowest SBM efficiency score in the evaluated sample rather than as a general conclusion that Cyprus is the most inefficient country in Europe.

SBM Slack Structure and Improvement Targets

The slack analysis reveals substantial heterogeneity in the sources of relative inefficiency. Cyprus exhibits particularly large shortfalls in Online E-Government Services and Satisfaction with eID, estimated at approximately 21.288 and 65.041 points, respectively in table 4 below.

Table 4. SBM Slack Structure for Countries with SBM Scores below 1

Country	SBM	Internet Slack	Govt. Slack	R&D Slack	Online Shortfall	eID Shortfall	Interaction Shortfall
Luxembourg	0.5256	8.213	4.956	7.558	0.000	19.945	24.802
Austria	0.6579	0.000	1.508	41.189	0.378	0.000	5.952
Belgium	0.5728	6.147	1.376	51.567	0.000	10.220	6.791
France	0.4748	3.387	1.644	30.442	0.000	39.055	16.198
Germany	0.4417	8.147	2.376	45.467	0.000	29.220	19.791

Netherlands	0.8036	0.000	2.389	8.188	2.519	0.000	0.000
Czech Republic	0.6765	7.561	0.000	15.119	0.000	26.745	5.487
Slovakia	0.7536	11.686	0.012	5.350	16.360	0.000	6.663
Bulgaria	0.4871	3.884	0.955	6.002	0.000	21.319	29.747
Romania	0.3358	18.829	0.164	0.000	9.961	36.667	36.101
Sweden	0.6093	0.000	3.496	33.272	11.078	9.158	0.000
Ireland	0.5395	6.147	2.576	10.167	0.000	37.220	1.791
Lithuania	0.7229	4.867	1.160	7.750	9.174	0.000	10.547
Slovenia	0.7186	5.097	0.000	24.836	3.914	10.998	0.000
Spain	0.7511	6.333	0.040	13.250	0.826	0.000	11.453
Croatia	0.8257	13.487	0.000	0.000	0.000	9.442	15.625
Cyprus	0.2117	23.732	0.203	4.044	21.288	65.041	0.000

Romania similarly displays sizeable shortfalls in eID Satisfaction and Interaction with Public Administration, at approximately 36.667 and 36.101 points. France and Ireland also exhibit large eID-related shortfalls, while Bulgaria records substantial deficiencies in both eID Satisfaction and Interaction with Public Administration. Slovakia's largest output shortfall is associated with Online E-Government Services, whereas Croatia's inefficiency is concentrated primarily in eID Satisfaction and administrative interaction.

These patterns indicate that relatively inefficient countries do not share a common deficiency structure. Consequently, the model does not support a uniform improvement strategy across the EU-27. The diagnostic contribution of SBM lies precisely in identifying which dimensions account for the distance between an inefficient DMU and the benchmark frontier.

Input slacks require cautious substantive interpretation because Internet usage, government support, and R&D capacity are generally desirable enabling conditions rather than undesirable resources that should necessarily be reduced. A positive input slack is therefore interpreted as evidence that the observed level of an enabling condition is not matched by proportionate output performance relative to the benchmark frontier. From a policy perspective, the relevant implication is to improve the conversion of existing digital capacity into observable public-service outcomes rather than to reduce socially desirable digital inputs.

Table 5. Selected SBM Output Projections

Country	Current Online	Target Online	Current eID	Target eID	Current Interaction	Target Interaction
Cyprus	56	77.288	8	73.041	62	62.000
Romania	50	59.961	20	56.667	12	48.101
France	90	90.000	46	85.055	56	72.198
Germany	87	87.000	53	82.220	50	69.791
Bulgaria	67	67.000	42	63.319	24	53.747
Ireland	87	87.000	45	82.220	68	69.791
Slovakia	63	79.360	75	75.000	57	63.663
Croatia	80	80.000	60	69.442	52	67.625

The projected output values provide a direct interpretation of the slack calculations in table 5. For Cyprus, the model-based benchmark requires Online E-Government Services to increase from 56 to approximately 77.288 and Satisfaction with eID to increase from 8 to approximately

73.041, while Interaction with Public Administration remains at the observed level of 62. For Romania, the projected values are approximately 59.961 for Online Services, 56.667 for eID Satisfaction, and 48.101 for Interaction with Public Administration. These projections indicate that Romania's relative inefficiency is concentrated primarily in user-facing and administrative-interaction outcomes rather than in R&D input excess.

The projections should be interpreted as DEA benchmark values rather than as deterministic policy forecasts. They identify performance levels implied by the observed frontier under the specified dataset and model; they do not establish that the projected outcomes would automatically follow from a particular policy intervention.

Cross-Model Interpretation and Consistency

The differences among the Bi-Objective MCDEA BCC, Super-Efficiency, and SBM results are theoretically consistent with the distinct optimisation objectives of the three models. The Phase-1 MCDEA model establishes overall relative frontier performance, Super-Efficiency refines the comparison among frontier units, and SBM identifies non-radial inefficiency after explicit incorporation of input and output slacks. Consequently, identical numerical rankings are neither required nor expected across the three analytical stages.

A supplementary rank-consistency check was conducted for the 25 countries with both Phase-1 MCDEA and SBM scores. The Spearman rank correlation between the two sets of efficiency estimates was positive but moderate ($\rho = 0.377$, $p = 0.063$). This result indicates that the two measures retain some common ordering of country performance while also capturing materially different aspects of efficiency. The absence of a near-perfect rank association is therefore consistent with the methodological rationale for retaining both models rather than treating one as a substitute for the other. This cross-model comparison should be interpreted as a consistency assessment rather than as a formal sensitivity analysis of parameter perturbations.

Discussion

The findings reinforce the broader conclusion in the digitalisation literature that substantial cross-country variation exists in the efficiency with which European countries convert enabling conditions into digital public-service outcomes. İnel (2019), Yalçın (2021), Georgescu et al. (2022), and Krejnuš et al. (2023) similarly report heterogeneous digitalisation or e-government efficiency among EU countries. More recent studies have expanded this literature by combining DEA with tiered classification, network-readiness indicators, and productivity measures (Bánhidi & Dobos, 2023; Bánhidi & Dobos, 2024; Horváthová & Mokrišová, 2024).

The present study differs principally in the analytical roles assigned to the three DEA-based methods. Rather than presenting multiple models as alternative rankings, the sequential framework uses MCDEA to establish relative frontier performance, Super-Efficiency to discriminate frontier observations, and SBM to diagnose slack-sensitive inefficiency. This distinction is important because a single aggregate score may conceal the dimension responsible for relative underperformance. The country-specific slack profiles reported in Table 4 therefore provide information that is not available from the Phase-1 score alone.

The results should nevertheless be interpreted within the limits of deterministic DEA. The models establish relative performance with respect to the observed sample and selected indicators; they do not identify causal effects of government support, R&D, or digital access on national outcomes. Contextual explanations concerning infrastructure, policy quality,

institutional capacity, or innovation systems therefore require evidence external to the DEA calculations and should not be inferred directly from the efficiency scores.

Conclusion

This study evaluates the relative efficiency of digital transformation across the EU-27 using a sequential framework comprising the Bi-Objective MCDEA BCC Output-Oriented model, Super-Efficiency analysis, and the Slack-Based Measure. The three approaches are retained because they provide complementary rather than redundant information concerning frontier performance, discrimination among efficient units, and the specific slack structure underlying relative inefficiency.

With respect to the first research objective, Hungary and Portugal are identified as frontier-efficient under the Bi-Objective MCDEA BCC model, with both countries attaining an efficiency score of 1.000. The remaining 25 countries record Phase-1 scores below the estimated frontier. These findings represent relative efficiency within the specified EU-27 dataset and selected input-output structure and should not be interpreted as absolute measures of national digital development.

For the second research objective, Super-Efficiency analysis provides additional differentiation between the two Phase-1 frontier units. Portugal records a Super-Efficiency score of 1.009678, compared with 0.9999997 for Hungary, and therefore occupies the stronger position within the frontier set under the reported model specification.

For the third research objective, SBM reveals substantial heterogeneity in the sources of inefficiency. Cyprus records the lowest SBM score of 0.2117047 and exhibits particularly large shortfalls in Online E-Government Services and eID Satisfaction. Romania records an SBM score of 0.3357690 and displays sizeable shortfalls in eID Satisfaction and Interaction with Public Administration. Other countries show different combinations of input and output slacks, confirming that relatively inefficient DMUs do not require identical improvement priorities. Methodologically, the study demonstrates the value of separating relative-efficiency measurement, frontier discrimination, and slack-based diagnosis within a coherent sequential DEA framework. The contribution therefore extends beyond the production of another country ranking by providing multiple layers of efficiency information that can support more differentiated benchmarking of digital public administration.

Several limitations should be acknowledged. The analysis is cross-sectional and therefore does not capture changes in digital-transformation efficiency over time. The results are conditional on the three inputs, three outputs, and 27 EU countries included in the analysis. DEA is deterministic and does not establish causal relationships between the selected indicators and digital-transformation outcomes. In addition, the SBM projections represent model-based benchmark values rather than guaranteed policy outcomes. Future research may extend the analysis using longitudinal data, alternative indicator structures, formal sensitivity analysis, and dynamic productivity models.

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