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Measuring industry digital transformation with a composite indicator: A case study of the utility industry

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Abstract. Climate change, urban sprawl, a global pandemic, and the general trend of digitizing economies are driving the need for digital transformation of utilities. Policymakers of industry digital transformation need some aggregated metric that captures the essence of this multidimensional concept, identifies the pros and cons of current policies, and guides future directions based on cross-country benchmarking. This study develops the Industry Digital Transformation Index for the utility industry (IDTIu) as a composite indicator. IDTIu provides an aggregate score for the digital transformation of the national utility industry based on 31 indicators grouped into 8 sub-indices. IDTIu scores were calculated for 34

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European countries based on 2020 data. To avoid the methodological challenges of equal weighting and expert assessments, we applied the original Benefit-of-the-Doubt (BoD) model and its two extensions for the proportion and priority of sub- indices. Our results show that (i) the full flexibility of the original BoD model leads to the expected deficiencies in ranking leaders and assigning zeros to insignificant sub-indices; (ii) BoD model with ordinal sub-index share restrictions does not allow ranking of laggards when IoT, AI, and BDA are ranked as top 3 priorities. Therefore, at the current stage of the digital transformation of utilities, we recommend the BoD model with proportional sub-index share restrictions.

Keywords: digital transformation, composite index, Benefit-of-the-Doubt model, utility industry.

JEL Classification: C43, L97, M15, O33

1. INTRODUCTION

The utility industry includes companies that provide basic amenities such as electricity, gas, water supply, and sewerage. These enterprises important for people and governments face the same challenges around the world: the growing pressures of climate change, urban sprawl, aging infrastructure and workforce; and finally the global COVID-19 pandemic and related non-payments have significantly increased the financial pressure on utilities. In 2020, utilities executives ranked the top trends by impact as follows: (i) assure regulatory compliance and prepare for new market mechanisms, (ii) become digital organizations to meet customer expectations and grow, (iii) protect by cybersecurity, (iv) optimize operational costs and assets, and (v) change business and operating models to address distributed energy resources (Client Global Insights [CGI], 2020). Due to the financial chaos in utilities caused by the pandemic, preparing for new market mechanisms has lowered the priority of digitalization for customers and growth – a leader in 2018 and 2019. At the same time, 90% of utility executives report that they have developed some form of digital strategy, but only 10% obtain results from these strategies; and the main obstacle to transformation is cultural change and change management. Cultural differences and the digital divide consequently can be linked with age (Colombo et al., 2018), income groups (Stark, 2021), and other factors, however, their impact remains significant.

Policymakers of industry digital transformation need some aggregated metric that captures the essence of this multidimensional concept, identifies the pros and cons of current policies, and sets future directions based on cross-country and cross-industry benchmarking and tracking over time. As a measure of multidimensional phenomena, science offers composite indicators. However, the creation of reliable composite indices requires the selection and justification of their structural components, as well as statistical processing methods, which are often criticized (especially the need for normalization and an equal weighting scheme for aggregation).

The aim of this study is to create a composite indicator for measuring the digital transformation of the utility industry (IDTIu) using the Benefit-of-the-Doubt approach. The application of this approach allows us to rank countries by the level of digital transformation of the utility industry, as well as to identify the strengths and weaknesses of this process in the analyzed countries. The study calculates IDTIu 2020 scores for 34 European countries based on 31 indicators from the European Commission (2021) database on the digital economy for enterprises of electricity, gas, steam, air conditioning, and water supply (with 10 persons employed or more). This study contributes to a better understanding of (i) the digital transformation of the utility industry and (ii) methods for constructing a composite index to measure it. In addition, the proposed approach can be used to measure the digital transformation of other industries.

The remainder of the paper is organized as follows. Section 2 provides a literature review on composite indicators related to information and communication technology and the digital economy. Section 3 presents data selection and methodology for constructing IDTIu. Section 4 discusses the empirical results of assessing IDTIu scores for four weighting schemes. Section 5 concludes the study.

2. LITERATURE REVIEW

In the past two decades, interest in the development of composite indicators has grown, probably driven by globalization and digitalization. The literature (*e.g.*, Saisana & Tarantola, 2002; OECD, 2008; Greco, 2019) discusses in detail methodological approaches to developing composite indicators, as well as the pros and cons of certain mathematical and statistical procedures. In this review, we will focus on research on the development of composite indicators related to ICT and the digital economy. We are interested in both the set of indicators of the composite indicator and the procedure for their processing. First of all, it is the United Nations E-Government Development Index (EGDI), which has been published since 2001. The EGDI is a composite index based on a weighted average of three normalized sub-indices Telecommunications Infrastructure, Human Capital and Online Services (United Nations, 2020). It is important to note that before normalization (min-max), the indicators were standardized so that the EGDI is equally defined by 3 sub-indices and does not depend on the sub-index with the greatest dispersion. However, as the subsequent analysis shows, both equal weights (EW) and the normalization and standardization of indicators are criticized by many researchers.

Nevertheless, Desai *et al.* (2002), when developing the Technological Achievement Index (TAI), also used EW and normalized the indicator values using min-max normalization. At the same time, Desai *et al.* (2002, p. 11) note that "obvious drawback of this approach is that it complicates trend analysis". The TAI consists of 4 sub-indices (each with 2 indicators): Creation of technology, Diffusion of recent innovations, Diffusion of old innovations, Human skills. It is important to emphasize that the TAI focuses on outcomes and achievements rather than efforts or inputs, as the causal relationship between inputs and the results is not well known. However, we doubt the relevance of the proposed comparative global scale: leaders (TAI above 0.5), potential leaders (0.35–0.49), dynamic adopters (0.20–0.34), and marginalized (below 0.20). Obviously, with the spread of technology, the index values are gradually increasing, which requires a revision of this scale.

To measure e-business readiness, Nardo *et al.* (2004) developed a composite indicator, the so-called "e-business index", which consists of 12 basic indicators grouped into 2 sub-indices: Adoption and Use of ICT by business. Using three weighting schemes (EW, budget allocation process (BAP), and factor analysis (FA) weights), the authors confirmed that the ranking of countries is relatively stable. At the same time, inconsistencies in e-business development measuring still exist due to differences in approaches for e-business statistical reporting (Roshchyk et al., 2022).

In 2014, the Digital Economy and Society Index (DESI) was calculated for the first time – a composite indicator that examines Europe's digital performance (Foley *et al.*, 2020). The International DESI 2020 consists of 24 indicators that are grouped into 5 dimensions: Connectivity, Human Capital, Use Internet Services by Citizens, Integration of Digital Technology by Business, and Digital Public Services. Indicators are traditionally normalized by the min-max method, and when aggregating, weighted arithmetic average corresponding to the structure of the index were used.

Since 2017, the World Digital Competitiveness Ranking (WDCR) has been calculated (International Institute for Management Development [IMD], 2020). WDCR is a composite index that consists of 3 main factors (Knowledge, Technology, and Future readiness), each of which is divided into 3 sub-factors grouping 52 criteria. Each sub-factor, regardless of the number of criteria it contains, has equal weight when aggregated. But the weight of the criteria varies between types of data, namely: "hard criteria represent a weight of 2/3 in the overall ranking whereas the survey data represent a weight of 1/3" (IMD, 2020, p. 30). In addition, all criteria are standardized using STD, as in the case of EGDI.

Summarizing this part of the review, we emphasize that when constructing indices that are directly or indirectly related to digitalization, (i) in all cases a linear aggregation method was used, (ii) the attitude towards normalization (standardization) is ambiguous, (iii) equal weighting of indicators and/or sub-indices is standard practice. Nevertheless, OECD (2008), along with equal weighting, discusses the use of other methods for TAI. These are: principal components analysis and more specifically FA), BAP, BoD approach, unobserved components model, analytic hierarchy process. The study showed that the ratings of TAI countries based on different weighting methods are practically the same (with the exception of Singapore and Norway); Finland ranks first in all methods. This is consistent with the findings of Nardo *et al.* (2004) for e-business index.

In addition, when assessing the index of digitalization of financial services, Pakhnenko *et al.* (2021) calculated the weights of the indicators using the Fishburne formula. At the same time, when prioritizing indicators, the authors relied on their own judgments.

In general, when constructing a composite indicator, the choice of weighing method depends on the data and the analyst, but the relative importance of the indicators is a source of controversy (OECD, 2008). Obviously, confidence in the composite index will increase if weighting and aggregation methods are used that are independent of stakeholders. Moreover, EW allows countries to compensate for their weaknesses instead of pointing them out.

In this study, we use a BoD approach that, firstly, eliminates the subjective judgment of the analyst and experts as much as possible; second, it identifies the preferences (or opportunities) of national policy by assigning more weight to the indicators for which the country (unit) has the best performance. BoD approach is the data envelopment analysis (DEA) (Cooper *et al.*, 2011) in relation to the construction of composite indicators. The Benefit-of-the-Doubt approach got its name from Melyn and Moesen (1991), who applied the DEA to assess macroeconomic performance. The BoD approach is based on solving a linear programming problem to find indicator weights that maximize the composite index for each analysed country. Cherchye *et al.* (2007) applied BoD to the TAI construction and developed it by introducing additional restrictions on sub-index shares.

Subsequently, Gaaloul and Khalfallah (2014) used the BoD approach to reassess the Digital Access Index and confirmed that this approach is more suitable for drawing policy attention to bottlenecks. Rogge (2018) introduced into the BoD model a procedure for aggregating individual composite indicators into a group indicator using the example of the Human Development Index; this BoD extension is useful when analyzing groups of countries, regions, enterprises, etc. More recently, to reduce the complexity of the BoD-approach, Ravanos and Karagiannis (2020) develop it for the case where there are ideal and anti-ideal decision-making units. The proposed approach does not require solving linear programming problems and is illustrated for re-evaluating EGDI. Empirical results indicate that the authors' approach is probably more appropriate for EGDI purposes than equal weighting and the standard BoD approach.

In conclusion of the literature review, it should be noted that we did not find studies on the development of composite indices for digital transformation of industries. However, in the context of our article, the experience of building composite indexes using the BoD approach in the utility industry is interesting. These are: the construction of a composite index to measure Corporate Social Responsibility in the electricity utility industry by Paredes-Gazquez *et al.* (2016), as well as the index of sustainability of water companies by Perez *et al.* (2019).

Thus, the absence of composite indices to measure the digital transformation of industries motivated our study, and the findings of previous relevant studies determined our choice of the methodology for constructing such an index.

3. METHODOLOGY

The indicator chosen to measure the level of digital transformation of an industry is a composite indicator that we call the Industry Digital Transformation Index (IDTI). We follow the methodology for constructing composite indicators provided by the OECD (2008) when we develop IDTI: (1) theoretical framework, (2) data selection, (3) imputation of missing data, (4) multivariate analysis, (5) normalisation, (6) weighting and aggregation, (7) robustness and sensitivity, (8) back to the real data, (9) links to other variables, (10) presentation and visualisation.

To create the IDTI for the utility industry (IDTIu), we have collected data from the European Commission (2021) database on the digital economy for enterprises Electricity, gas, steam, air conditioning and water supply (10 persons employed or more). All indicators are measured as a percentage of enterprises. To understand the digital transformation of the industry, and also based on the grouping in the database, we introduced 8 sub-indices: Integration of internal processes (IIP, initially included 4 basic indicators), Integration with customers/suppliers, supply chain management (ICS, 6), Cloud computing services (CCS, 15), Big data analysis (BDA, 8), Artificial intelligence (AI, 4), Internet of Things (IoT, 7), Security policy: measures, risks and staff awareness (Security, 10), Enterprises that provided training to develop/upgrade ICT skills of their personnel (Training, 3).

The database (European Commission, 2021) contains information for 35 countries, but for Malta most of the data is missing, so we excluded it from the analysis. We used data from the previous year to fill in some of the missing data for 2020. We support that the lack of data for the entire observation period usually indicates that there are few digital transformations; in these cases we use the zero value of the missing indicator as in Desai *et al.* (2002). In addition, there are countries that currently do not use some technologies (the indicator value in the database is zero). For example, for Montenegro, the values of the indicators of the AI sub-index (Analyse big data internally using machine learning, Analyse big data internally using natural language processing, natural language generation or speech recognition, Use service robots, Enterprises with a chat service where a chatbot or a virtual agent replies to customers) are zero.

When conducting multivariate analysis of basic indicators, we limited ourselves to the analysis of the correlation matrix (to use the PCA, more available data is required to be meaningful (Nardo *et al.*, 2004)). The lack of correlation is useful because it means that the indicators measure different "statistical dimensions" of the data (Saisana & Tarantola, 2002). After excluding one of a pair of highly correlated indicators or overlapping indicators in different sub-indices, we got a final set of 31 indicators, which is shown in Table 1. However, for representativeness, we keep the IoT indicators despite the fact that the indicator Use smart meters, smart lamps, smart thermostats strongly correlates with Use movement or maintenance sensors (0.840), with Use sensors or RFID tags (0.844), and with Use other devices or systems of the IoT (0.907).

Following previous research (*e.g.*, Nardo *et al.*, 2004; Cherchye *et al.,* 2007; OECD, 2008) we do not standardize or normalize indicators, because they are all measured in percentages. Normalization is more likely to confuse the problem, as information inherent in percentages can be lost; in addition, standardized values are not recommended for BoD weighing (OECD, 2008). But we will check if normalization/standardization affects countries' ranking.

We use two weighting schemes: EW and the BoD. In the case of EW, sub-indices, regardless of the number of indicators they contain, have equal weight in the composite index, *i.e.* $w_i = 1/8$. The weights of the basic indicators within the sub-indices are also equal. The aggregation method is linear.

Table 1

Final structure of IDTIu-2020: Sub-indices and basic indicators

1. Integration of internal processes (IIP)
Enterprises who have ERP software package to share information between different functional areas
Enterprises using software solutions like CRM
2. Integration with customers/suppliers, supply chain management (ICS)
Enterprises sending e-Invoices, suitable for automated processing
Enterprises sending e-Invoices, not suitable for automated processing
Enterprises sending paper invoices
3. Cloud computing services (CCS)
Buy only medium CC services (e-mail, office software, storage of files, hosting of the enterprise's database)
Buy high CC services (accounting software applications, CRM software, computing power)
4. Big data analysis (BDA)
Analyse big data from smart devices or sensors (BDASDS)
Analyse big data from geolocation of portable devices (BDALOC)
Analyse big data from other sources (than BDASDS, BDALOC, BDASocialMedia)
Analyse big data internally using any method (of BDAML, BDANL, BDAOM)
5. Artificial intelligence (AI)
Analyse big data internally using machine learning (BDAML)
Analyse big data internally using natural language processing, natural language generation or speech recognition (BDANL)
Use service robots
Enterprises with a chat service where a chatbot or a virtual agent replies to customers
6. Internet of Things (IoT)
Use smart meters, smart lamps, smart thermostats to optimise energy consumption in the enterprise's premises
Use sensors, RFID or IP tags or internet-controlled cameras to improve customer service, monitor customers' activities or offer them a personalised shopping experience
Use movement or maintenance sensors to track the movement of vehicles or products, to offer condition-based maintenance of vehicles
Use sensors or RFID tags to monitor or automate production processes, to manage logistics, to track the movement of products
Use other IoT devices or systems
7. Security policy: measures, risks and staff awareness (SP) ICT security measure used:
strong password authentication
keeping the software (including operating systems) up-to-date
user identification and authentication via biometric methods implemented by the enterprise
encryption techniques for data, documents or e-mails
data backup to a separate location (including backup to the cloud)
network access control
Virtual Private Network (VPN)
maintaining log files for analysis after security incidents
ICT risk assessment (assessment of probability/consequences of ICT security incidents)
ICT security tests
8. Enterprises that provided training to develop/upgrade ICT skills of personnel (T)
Enterprise provided training to their personnel to develop their ICT skills

Source: European Commission (2021); own compilation

When applying the BoD approach (Cherchye *et al.*, 2007), we calculate the composite IDTIu for country *c* by solving the following linear programming problem:

$$IDTIu_c = \max \sum_{i=1}^{m} w_{c,i} y_{c,i} \tag{1}$$

$$\text{s.t.} \sum_{i=1}^{m} w_{c,i} y_{j,i} \leq 1, \quad j = \overline{1;n}; \tag{2}$$

$$w_{c,i} \geq 0, \quad i = \overline{1;m}, \tag{3}$$

where $w_{c,i}$ and $y_{c,i}$ are the weight and value of sub-index *i* for the analyzed country *c*.

Composite indicator, as in the case of EW, is the sum of the shares of sub-indices $w_{c,i}y_{c,i}$, but the BoD model (1-3) finds weights that maximize the composite indicator for each country under analysis. Constraint (2) is that no other country under analysis has a composite index greater than 1 when using the optimal weights for the country being assessed (Cherchye *et al.*, 2007). The original BoD model (1-3) assumes absolute flexibility in weighing, that is, the “country” assigns maximum weights to those sub-indices / areas of digital transformation, where it has achieved the greatest success. But as a result, we can get shares equal to zero and 1, as well as composite index values equal to 1 for more than one country. To minimize the risk of overestimating or underestimating sub-index shares, we introduce the following proportional constraint into model (1-3):

$$\frac{w_{c,i} y_{c,i}}{\sum_{i=1}^{m} w_{c,i} y_{c,i}} \leq \alpha . \tag{4}$$

Note that in constraint (4) we do not indicate the lower bound, since at the current stage of digital transformation, some sub-indices for some countries are equal to zero. In addition, problem (1-4) is a nonlinear programming problem.

BoD models (1-3) and (1-4) assign the highest weights to the sub-indices with the highest actual values, reflecting government and industry policy on utilities. However, political and public importance often differs. We use a BoD approach to avoid the subjectivity of expert judgments, but to reflect the priority areas of digital transformation of utilities, we consider it possible to add a “limited agreement” on the importance of sub-indexes, following Cherchye *et al.* (2007). This is a sequence of ordinal constraints like “sub-index A is less important than sub-index B”. Based on a survey of roughly 300 stakeholders in the water and wastewater sector (Wallis-Lage, 2020), interviews with 97 executives in the electricity, water and waste management and downstream gas sectors (CGI, 2020), survey of 65 respondents (Detwiler, 2019), and Sensus (2018), we have compiled the following ordinal constraints on the shares of sub-indices:

$$\begin{aligned} & w_{c,T} y_{c,T} \leq w_{c,ICS} y_{c,ICS} \leq w_{c,SP} y_{c,SP} \leq w_{c,IIP} y_{c,IIP} \leq \\ & \leq w_{c,CCS} y_{c,CCS} \leq w_{c,BDA} y_{c,BDA} \leq w_{c,AI} y_{c,AI} \leq w_{c,IoT} y_{c,IoT} . \end{aligned} \tag{5}$$

We use Excel Solver to solve optimization problems and sensitivity analysis. For analytical purposes, we propose to group countries by the level of digital transformation of the utility industry, since a wide range of IDTIu scores is expected. We distinguish 4 groups of countries using the terms of Desai *et al.* (2002), but we replace the "marginalized" countries with a softer term – "laggards". For the comparative scale, we suggest using the sigma interval principle: leaders (IDTIu above $\mu+\sigma$), potential leaders (μ; $\mu+\sigma$), dynamic adopters ($\mu-\sigma$; μ), and laggards (below $\mu-\sigma$), where μ is the average IDTIu for the analyzed countries, σ is the standard deviation.

4. EMPIRICAL RESULTS AND DISCUSSION

The results of calculating IDTIu for different weighting schemes and ranking countries are shown in Table 2. Figures 1-4 visualize the shares of IDTIu for Finland, Belgium, and Poland. We have selected these countries to visually demonstrate changes in scores and country rankings for different weighting schemes.

Table 2

Country scores of the IDTIu and ranking for different weighting schemes

Country	Code	Equal weights		BoD model (1-3)		BoD model (1-4)		BoD model (1-3, 5)	
		score	rank	score	rank	score	rank	score	rank
Austria	AT	0.151	33/lg	0.619	29/lg	0.539	29/lg	0	24-34/lg
Belgium	BE	0.252	20/da	0.972	7/l	0.889	8/pl	0.282	20/da
Bosnia and Herzegovina	BA	0.166	32/lg	0.591	32/lg	0.483	32/lg	0	24-34/lg
Bulgaria	BG	0.173	30/lg	0.602	31/lg	0.453	33/lg	0.205	22/da
Croatia	HR	0.293	13/pl	0.967	10/pl	0.729	19/da	0.508	10/pl
Cyprus	CY	0.246	22/da	0.666	26/da	0.652	22/da	0.402	19/pl
Czech Republic	CZ	0.298	11/pl	0.827	17/pl	0.782	14/pl	0.488	12/pl
Denmark	DK	0.317	5/pl	0.970	8/pl	0.933	5/l	0.597	6/pl
Estonia	EE	0.299	10/pl	0.875	16/pl	0.768	15/pl	0.683	5/l
Finland	FI	0.422	2/l	1	1-6/l	1	1-3/l	1	1/l
France	FR	0.256	19/da	0.788	20/da	0.749	16/pl	0.455	15/pl
Germany	DE	0.298	12/pl	0.900	15/pl	0.847	10/pl	0	24-34/lg
Greece	GR	0.179	29/lg	0.584	33/lg	0.549	28/lg	0.019	23/lg
Hungary	HU	0.228	24/da	0.724	23/da	0.575	25/da	0.445	16/pl
Iceland	IS	0.240	23/da	0.912	14/pl	0.813	13/pl	0	24-34/lg
Ireland	IE	0.301	9/pl	0.936	12/pl	0.830	12/pl	0	24-34/lg
Italy	IT	0.276	16/pl	0.766	22/da	0.716	20/da	0.557	9/pl
Latvia	LV	0.250	21/da	0.775	21/da	0.650	23/da	0.443	17/pl
Lithuania	LT	0.281	14/pl	0.827	18/pl	0.735	18/pl	0.490	11/pl
Luxembourg	LU	0.310	6/pl	0.937	11/pl	0.892	7/pl	0	24-34/lg
Montenegro	ME	0.205	26/da	0.672	25/da	0.571	27/da	0	24-34/lg
Netherlands	NL	0.343	4/l	1	1-6/l	0.970	4/l	0.716	4/l
North Macedonia	MK	0.111	34/lg	0.544	34/lg	0.402	34/lg	0	24-34/lg
Norway	NO	0.419	3/l	1	1-6/l	1	1-3/l	0.857	3/l
Poland	PL	0.259	18/da	0.710	24/da	0.693	21/da	0.472	14/pl
Portugal	PT	0.279	15/pl	0.967	9/pl	0.898	6/pl	0.583	8/pl
Romania	RO	0.189	27/da	0.607	30/lg	0.518	31/lg	0.242	21/da
Serbia	RS	0.186	28/lg	0.627	28/lg	0.518	30/lg	0	24-34/lg
Slovakia	SK	0.274	17/pl	0.819	19/pl	0.746	17/pl	0.474	13/pl
Slovenia	SI	0.308	7/pl	1	1-6/l	0.860	9/pl	0.410	18/pl
Spain	ES	0.306	8/pl	0.915	13/pl	0.840	11/pl	0.595	7/pl
Sweden	SE	0.427	1/l	1	1-6/l	1	1-3/l	0.874	2/l
Turkey	TR	0.168	31/lg	0.652	27/lg	0.607	24/lg	0	24-34/lg
United Kingdom	GB	0.216	25/da	1	1-6/l	0.574	26/lg	0	24-34/lg

l, pl, da, and lg are leaders, potential leaders, dynamic adopters, and laggards, respectively.
Source: own calculations

As we expected, the original BoD model gives significantly higher IDTIu scores than the EW scheme, because when weighing BoD, countries use their competitive advantages in digital transformation over other analyzed countries. For example, Belgium increased the score from 0.252 to 0.972 and moved up from 20th to 7th position, due to Artificial Intelligence ($y_{BE,AI}$ = 0.048 is the second value after Norway $y_{NO,AI}$ = 0.053); Great Britain increased the score from 0.216 to 1 and moved up from 25th position to 1st (more precisely 1-6) due to the maximum Training-value among the analysed countries ($y_{GB,T}$ = 0.699). However, countries whose sub-indices are at a great distance from the maximums (goalposts) have downgraded their ratings. For example, in Polish utilities, the ICS and SP sub-indices have the smallest distances to the maximums, namely, 35.4% and 29.0% less than the maximums, respectively. For comparison, in Belgium, the AI sub-index is less than the maximum by 9.5%.

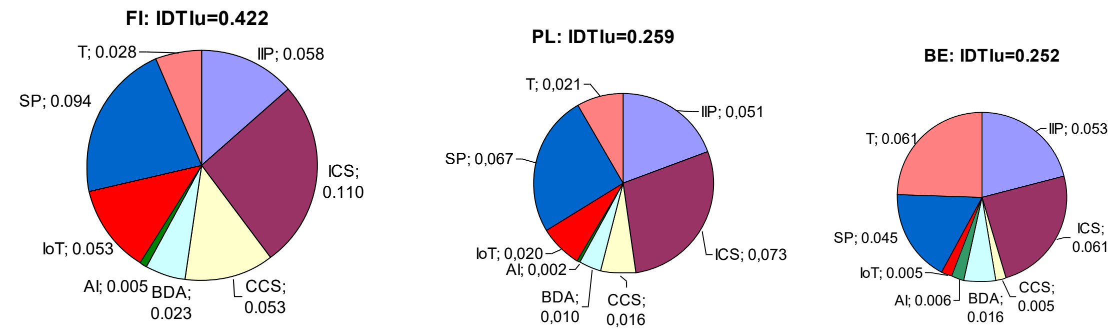


Figure 1. IDTIu structure based on the equal sub-index weights

Source: own calculations

At the same time, Table 2 and Figure 2 show the expected undesirable consequences of the fully flexible BoD model (1-3): (i) for 6 countries IDTIu = 1; (ii) model decisions are unrealistically high weights for the sub-indices with the highest relative importance to the country and therefore their share (*e.g.*, IDTIu for Finland is 95.7% ICS and 4.3% IoT; IDTIu for Belgium is 73.5% AI and 26.5% Training; IDTIu for Poland is 98.8% Security policy and 1.2% ICS).

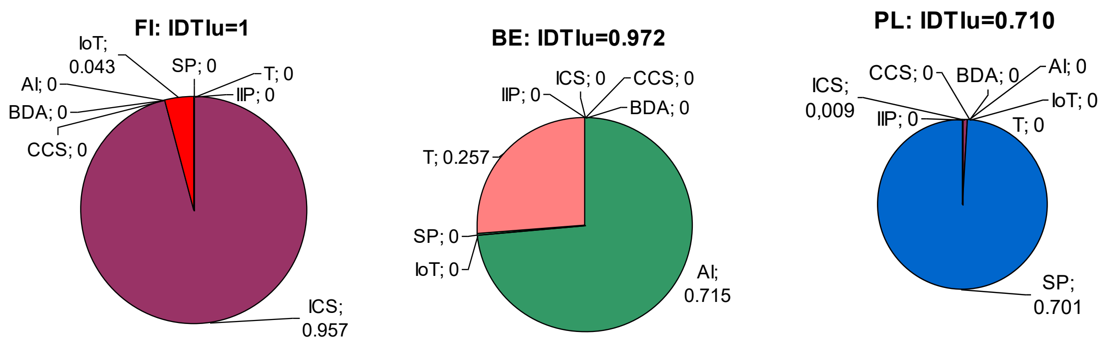


Figure 2. IDTIu structure based on the original BoD model

Source: own calculations

To eliminate this drawback, we added constraint (4) with a = 0.3, i.e. limited the percentage of sub-indices to 30%. The tightening of restrictions led to a decrease in IDTIu for all countries except the 3 leaders

(Finland, Norway, and Sweden); nevertheless, 15 countries improved their ranking. We have obtained a more realistic structure of the indices, probably in many cases the upper bounds are actually mandatory (Cherchye *et al.*, 2007).

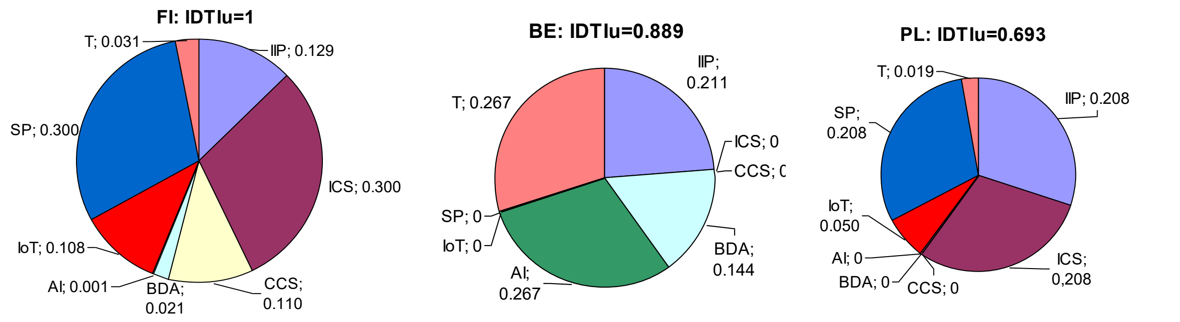


Figure 3. IDTIu structure based on the BoD model with proportional sub-index share restrictions
Source: own calculations

Note that we also used α = 0.2. In general, we received a similar rating with an index equal to 1 for the same three leaders. But for Iceland, there is no feasible solution to the programming problem, given the mutual incompatibility of such constraints; the reason is zero values of IoT, AI, BDA, SP. Thus, as Cherchye *et al.* (2007) warned, constraints prevent indicators from being overestimated or underestimated, but they should be used with caution.

To reflect the importance of sub-indexes in terms of digital transformation of utilities, we solved BoD problem (1-3) with ordinal constraint (5). This hard constraint (in conditions when utilities in many countries do not use or only slightly use the IoT, AI, BDA) led to a significant decrease in scores and only Finland has a IDTIu = 1. In Finnish utilities, the IoT sub-index is 0.420, followed by Latvia with a value of 0.186 (i.e., 55.7% less). As a result, Latvia has moved to the group of potential leaders, but Latvian utilities practically do not use AI and BDA (0,005 and 0,065, respectively), therefore only 17th place in the ranking. As Figure 3 shows, Poland has also managed to get ahead of Belgium through the use of IoT. For Polish utilities, the IoT sub-index is 0.186, and for the Belgian only 0.042. As a consequence, Poland moved into the group of potential leaders, and Belgium fell into the group of adopters. However, Polish utilities use Artificial Intelligence and Big Data Analysis less than Belgian ones.

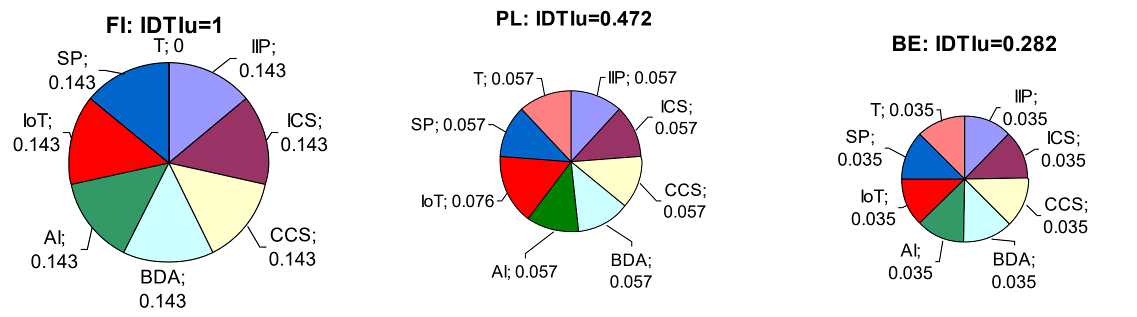
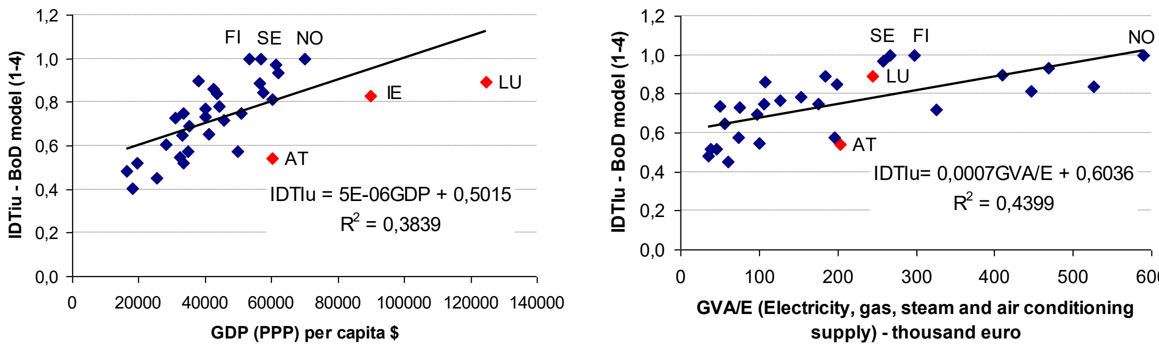


Figure 4. IDTIu structure based on the BoD model with ordinal sub-index share restrictions
Source: own calculations

Thus, this latest rating is the best signal of miscalculations in the top directions of the digital transformation of the utility industry. On the other hand, at the current stage of the digital transformation of utilities, the BoD model with proportional sub- index share restrictions provides a multidimensional assessment for countries with different levels of digitalization.

It should be noted that we applied the BoD approach to standardized and then normalized data (like United Nations (2020)) to test the undesirable effects of these procedures on ranking, as indicated, for instance, by Cherchye *et al.* (2007) or Mariano *et al.* (2021). In our case, the rating changed insignificantly, with the exception of Spain (up 6 positions) and Portugal (down 5 positions). Standardization led to the fact that approximately equal actual values of the AI sub-index for Spain (0.045) and Portugal (0.048) took significantly different values (1.185 and 0.108, respectively). The main reason is that chatbot usage by Portuguese utilities is 0.9 p.p. below average. As a result of BoD optimization, the share of AI in the index increased from 0.363 to 0.700 for Spain and decreased from 0.695 to 0,000 for Portugal.

The final analytical stage examines the relationship between the composite index and macroeconomic and industry indicators, as well as related indices. Figure 5 (a) supports our assumption that countries with high GDP per capita will have high IDTIu scores. However, Luxembourg and Ireland, and to a lesser extent Austria, are clear outliers. Findings for Ireland and Austria are consistent with the TAI pattern (OECD, 2008): average technological advances with high GDP per capita. As for Luxembourg, in 2020, 0% of utilities used Artificial Intelligence (BDAML, BDANL, robots and chat services), data on all IoT indicators are not available (European Commission, 2021), and all BDA indicators are below average. At the same time, Figure 5 (b) shows that, in contrast to GDP, Luxembourg lags behind the leaders in digital transformation in terms of gross value added per person employed in utilities (for 2018).



(a) (b)

Figure 5. Relationship between IDTIu and (a) GDP per capita and (b) GVA per employee

Source: own calculations

Furthermore, the World Digital Competitiveness Ranking (IMD, 2020) confirms the challenges of digital transformation in general (Luxembourg is 14th among the countries we analyze). The correlation coefficients between World Digital Competitiveness Ranking and IDTIu are 0.599, 0.627, 0.664, and 0.295 for EW and three BoD models, respectively. In addition, the leaders in the digitalization of financial services rankings (Pakhnenko *et al.*, 2021) Denmark, the Netherlands, Finland, Sweden, and Norway, with the exception of the United Kingdom, are the leaders in the digital transformation of utilities. The low position of the United Kingdom in our rankings, with the exception of the original BOD model, is explained by the following: 0% of utilities conduct Analyze big data internally using machine learning; 0% of utilities conduct Analyze big data internally using natural language processing, natural language generation or speech recognition; 1% of utilities with a chat service where a chatbot or a virtual agent replies to customers; 2%

of utilities use service robots; and IoT data is not available. Finally, Finland ranks first for all BoD models, which is consistent with TAI (OECD, 2008) and I-DESI (Foley *et al.*, 2020).

5. CONCLUSION

By developing an Industry Digital Transformation Index for the utility industry, this study contributes to a better understanding of (i) industry digital transformation and (ii) techniques for constructing a composite index to measure it. IDTIu is a composite index of 31 indicators grouped into 8 sub-indices. To avoid the methodological challenges of equal weighting and expert assessments, we applied the original BoD model (Cherchye *et al.*, 2007) and two extensions: with proportional and ordinal sub-index share restrictions. Our empirical results show that (i) the full flexibility of the original BoD model leads to the expected deficiencies in ranking leaders and assigning zeros to insignificant sub-indices; (ii) BoD model with ordinal sub-index share restrictions does not allow ranking of laggards when IoT, AI, and BDA are ranked as top 3 priorities. Therefore, at the current stage of the digital transformation of utilities, we recommend using the BoD model with proportional sub-index share restrictions. In this case, IDTIu's structure and ranking are most informative for government and industry policy makers, as it best signals the strengths and weaknesses of utilities digital transformation. Moreover, on this model IDTIu scores show the greatest correlation with macroeconomic and industry indicators, as well as related indices. Following Foley *et al.* (2018) we refrain from making recommendations based on simple comparisons between countries, as many countries have economic and cultural reasons for more or less use of digital technology in utilities.

The structure of IDTIu is not static and will obviously change as the utilities are digitally transformed. The proposed approach can be used to develop composite digital transformation indices for other industries.

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