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Re-evaluating electronic government development index to monitor the transformation toward achieving sustainable development goals

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ABSTRACT

While the connection between the electronic government development index (EGDI) and sustainable development goals (SDGs) is well established, global efforts to provide appropriate means for achieving SDGs remain insufficient. This study addresses this issue by introducing a hybrid framework using Shannon entropy to derive data-driven weights for aggregation, technique for order preference by similarity to ideal solution for relative ranking, and data envelopment analysis for generating performance efficiency and effectiveness indices, benchmarks for setting targets, and analytical insights for smarter decisions and managerial actions. The hybrid methods are validated on the 2014, 2016 and 2018 EGDI datasets that cover 193 countries. Our findings illustrate a significant change in the weights of performance indices, leading to a change in the ranks of over 90% of the countries, and a decrease in the SDG performance trend due to less efficient utilization of resources, despite an increase in the effectiveness of outcomes.

1. Introduction

Building on the principle of "leaving no one behind," the 2030 agenda for sustainable development (SD) was launched in 2015 by the United Nations (UN) member states to end poverty and set the world on a path of peace, prosperity, and opportunity for all on a healthy planet. SD aims to meet human development goals while simultaneously sustaining the ability of natural systems to provide the natural resources and ecosystem services on which the economy and society depend (Wikipedia, 2020). It includes 17 SD goals (SDGs) and 169 targets. The SDGs call for the transformation of the financial, economic, and political systems that govern countries (UN-SDA, 2015). However, the 2020 UN survey report on progress made toward achieving the SDGs recognized that the *global efforts* to date have been *insufficient* to deliver the needed transformation worldwide (UN-SDGR, 2020), and exhorted the world to act by outlining a roadmap for governments to achieve modern data systems for SDGs (Espey, Badiee, Dahmm, Appel, & Noe, 2019). This deficiency in global efforts would jeopardize the 15-year plan to achieve the SDGs. The report called for renewed ambition, mobilization, leadership, and collective action by all stakeholders to ensure that statistical organizations have the *right tools and resources* to facilitate the timely transformation, monitoring progress, and smart decision-making to achieve the SDGs.

The connection between SDGs and electronic government (EG) has been well established (Estevez & Janowski, 2013; Schuppan, 2009). EG provides a platform for the digital transformation of public administration through the delivery of government information services to stakeholders using digital technologies, such as the Internet and social media as well as traditional modes (Osman et al., 2019). Janowski (2015) argued that EG has been continuously evolving into digital government (DG) in ways to find innovative digital solutions to social, economic, political, and other pressures, for which, the author proposed a four-stage evolution model: the digitization stage where technology in government (TiG) has no internal and external transformation features; the transformation stage of EG where TiG impacts internal government transformation; the engagement stage (electronic governance) where TiG impacts both internal government transformation and external relationship transformation; and the contextualization stage (policy-driven electronic governance) where TiG impacts various sectors and communities. Further, Janowski (2016) emphasized that DG and public governance are key implementation means for achieving SDGs. Similarly, Marcovecchio, Thinyane, Estevez, and Janowski (2019) reported that DG is the implementation means for achieving SDGs. Schmidt-Traub, Kroll, Teksoz, Durand-Delacre, and Sachs (2017) introduced the SDG index and dashboards as analytical tools for assessing SDGs progress baselines at the country level. Additionally, EG has ultimately been

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the creator of public values through improved public services, administration, and environmental and social values among other SDG outcomes (Osman et al., 2019; Osman, Anouze, Irani, et al., 2014; Panagiotopoulos, Klievink, & Cordella, 2019; Twizeyimana & Andersson, 2019).

Given the importance of EG development in supporting the transformation toward sustainable and resilient societies, in 2001, the UN Department of Economic and Social Affairs (DESA) launched the electronic government development index (EGDI), which measures countries' use of information and communications technologies (ICT) to deliver public services (Chung, 2019). EGDI is composed of three sub-indices, namely, the telecommunication infrastructure index (TII), human capital index (HCI), and online service index (OSI) (UN-G, 2018). The benefits of EGDI and its sub-indices have been widely reported in the literature. The OSI sub-index is used as a proxy measure of the level of transformation achievement on SDGs by each country (Hub, 2018; Janowski, 2016). The OSI and TII sub-indices are found to be significant predictors of the entrepreneurship level in any country (Abu-Shanab & Osmani, 2019). The ICT role of the TII sub-index was deemed essential for accelerating actions on SDGs (UN-ICT-SDGs, 2016; Wu, Guo, Huang, Liu, & Xiang, 2018).

Despite the tremendous benefits of both EG and EGDI, several challenges related to their evaluations with suggested approaches to improve have been reported. *On the SDG side,* Janowski (2016) reported that the *gap between the SDG aspirations* (*targets*) and the *resource capacity* of DG affects more than 69% of the UN member states. Understanding and eventually addressing this issue requires *further research efforts* on benchmarking methods to establish best practices for sustainable improvement. Wu, Guo, et al. (2018) revealed that research on how SDGs can be achieved using the ICT indicators of EGDI is very limited and called for more global scientific, technological, industrial, and governmental efforts to promote and support the future achievement of SDGs. Marcovecchio et al. (2019) identified that the measurement of indicators toward progress is one of the challenges for achieving SDGs. Moreover, Diaz-Sarachaga, Jato-Espino, and Castro-Fresno (2018) discussed further limitations of SDG evaluation techniques: a biased selection of indicators that can favor specific countries, inefficiency in the data collection process, lack of some metrics that could impact achieving certain goals, and lack of a *holistic view* of countries' performance. The authors called for the creation of a more customized evaluation of SDGs that caters to regional needs.

On the EGDI side, its evaluation and implementation have certain limitations. The 2018 UN E-government survey (UN-G, 2018) emphasized the need to strengthen the online-based information service *provision*, policy *participation*, and *decision-making* integration (Chung, 2019). Strategies should be established to accelerate administrative innovation using *intelligent insights* in the smart information processing age. Further, Skargren (2020) reviewed the criticism of benchmarking techniques of EG and their lack of usefulness and suggested that *benchmarking* of EG development needs to be more attuned to *empirical findings* and *more sensitive* to both the *context of public administration* and the inherent challenges of EG.

On the methodology side, the derivation of EGDI scores uses equal weighting of indices based on expert opinions that may be prone to bias and unrealistic results (Suh, Park, & Kang, 2019). To address this limitation, Whitmore (2012) suggested using statistical approaches to derive data-driven weights for aggregating indices. In addition, existing aggregation methodologies are based on the *absolute* ranking of countries, thereby leading to an intense race among countries with no *empirical insights* for benchmarking and managerial actions (Crespo & Crespo, 2016; Skargren, 2020). Furthermore, the performance measures to assess the efficiency of utilization of input resources and the effectiveness of outcomes are missing from EG research. Osman et al. (2019) suggested developing *efficiency* and *effectiveness* indices based on a *relative* benchmarking of countries to guide the EG transformation. Choi and Park (2019) used the data envelopment analysis (DEA) to model the efficiency performance of countries on the social progress index, which uses EGDI scores as inputs. They argued that developing countries require some performance guidance on the usage of EG resources to improve social progress. The analytical hierarchy process (AHP) was proposed to identify weights using expert opinions on the importance of indicators used to improve EG services (Choi, Park, Rho, & Zo, 2016; Hassan & Lee, 2019). Several other scholars have also studied the importance of indicators for EG development using logistic regression models (Dias, 2020; Siau & Long, 2009) and structured equation models (Whitmore, 2012).

Based on the above brief literature review identifying gaps, limitations, and recommendations, in this paper, we aim to contribute to addressing some of these challenges to support countries in their EG transformation initiatives toward achieving SDGs. *First*, the Shannon entropy (SE) approach is proposed to determine data-driven weights based on the importance of the contribution of each index to aggregate the EGDI sub-indices and address the equal weighting challenge (Shannon, 1948). *Second*, the technique for order preference by similarity to ideal solution (TOPSIS) is implemented as an alternative relative ranking approach of countries. It determines the position of a country based on the closeness of each country score to the *best* ideal solution (BIS) and the *worst* ideal solution (WIS) or the best and worst ideal countries. Hence, it provides a *better relative benchmarking* approach (Hwang & Yoon, 1981). *Third*, the DEA method is applied to model the performance of EG *transformation* of each country relative to the performance transformation of other countries; it uses the multiple values of the EGDI sub-indices to determine such performance transformation scores (Charnes, Cooper, & Rhodes, 1978). However, the novelty of our DEA model is the introduction of two DEA performance transformation scores to generate significant analytical insights for better guidance of EG transformation toward achieving SDGs. This includes an *input-efficiency* score, which measures the efficiency of utilization of technology and human capital resources, and the *output-effectiveness* score, which measures the effectiveness of both the generated outputs of the online services and the impact of their outcomes on SDGs. The novel DEA implementation was applied to reassess EGDI for the first time in the EG literature. The DEA results would help in empirically identifying the best-practice benchmark of peers (set of efficient countries). The empirical benchmark would then be used to set *improvement targets* for inefficient countries. Further, the DEA method would optimize the weights of the EGDI sub-indices each time in the best interest of the country being evaluated. Consequently, the DEA results would be *more sensitive* to the local EG context (vision, strategy, plan, initiatives, and challenges) of each country. Such sensitivity would lead to more motivation and better alignment of global efforts toward achieving SDGs. Last, the various hybrids are validated on data collected for 193 UN member states for the last three evaluation periods in 2014, 2016, and 2108. We discovered a significant change in the weights of the performance indices, leading to a change in the ranks of over 90% of the countries, and a decrease in the SDG performance trends due to less efficient resource utilization, despite an increase in the effectiveness of outcomes. This indicates that the world is producing the current SDG outcomes at the expense of less efficient use of resources. Further investigation should be undertaken to support nations in achieving a better sustainable growth when realizing their SDGs.

The remainder of the paper is structured as follows. Section 2 provides a review of the related work on existing challenges about the current approaches for evaluating EGDIs and SDGs. Section 3 presents our proposed methods. Section 4 describes our empirical findings and analytics results. Section 5 offers further discussions, and Section 6 concludes the study and identifies future research directions.

2. Background and related work

This section provides a review of the evaluation methods applied in the context of EGDI and SDGs. The aim is to identify challenges, gaps,

and limitations that have hitherto prevented the EG transformation toward achieving the desired targets for SDGs.

2.1. Evaluation methods of EGDI and SDGs

The Web of Science database is used to identify the relevant research publications. The terms EGDI or "electronic government development index" were used in the search for publications since the inception of EGDI in 2001. The search resulted in 193 documents. Filtering the search with a focus on peer-reviewed journals (PRJs) resulted in 19 open access and 92 regular publications, of which, 79 PRJs adopted qualitative approaches and only 33 PRJs adopted quantitative approaches. In this subset, 11 PRJs focused on data collection and surveys around EG improvement, and 22 papers focused on new ways and models to analyze EGDI. These are presented in Table 1.

The list reflects that research assessments with a focus on EGDI have recently emerged. We observe that most scholars in the context of EGDI investigated the relationship of EGDI with new contexts involving the addition of new variables that may contribute further to EG development. For instance, such variables include the gross domestic product (Dias, 2020); entrepreneurship (Abu-Shanab & Osmani, 2019); education, digital skills, and Internet access (Lytras & Şerban, 2020); trust, income levels, and ICT (Park & Oh, 2018); corruption (Chen & Aklikokou, 2019; Máchová, Volejníková, & Lněnička, 2018); digital economy (Ali, Hoque, & Alam, 2018); environment sustainability (Lee, 2017); and culture (Hatmanu, Lobont, Albu, & Moldovan, 2014; Zhao, Shen, & Collier, 2014); while new evaluation models based on survey data were proposed as alternative ways to measure EG development (e.g., Choi et al., 2016; Hassan et al, 2019; Perdał, 2016) and indices (e.g., Yera, Arbelaitz, Jauregui, & Muguerza, 2020). For instance, Choi and Park (2019) developed a DEA model to explore the impact of EGDI values on the social progress index of countries. It is evident from the above comprehensive review that no study considered the reassessment of EGDI methodologies for generating transformation insights and identifying benchmarking tools to set targets for improvement and motivating countries to achieve SDGs.

Similarly, a review on SDGs showed a recent research interest in evaluation methods. Table 2 provides the list of hybrid combinations, consisting of more than one evaluation methods. From the table, it can be observed that only 7 out of 17 SDGs have attracted individual research attention. The remaining 10 SDGs, (i.e., no poverty [SDG 1], zero hunger [SDG 2], quality of education [SDG 4], gender equality [SDG 5], clean water and sanitation [SDG 6], decent work and economic growth [SDG 8], reduced inequality [SDG 10], life below water [SDG 14], peace, justice, and strong institutions [SDG 16], and partnerships for goals [SDG 17]) have not been evaluated individually but are indirectly evaluated through the EGDI survey. However, no prior hybrid performance evaluation method exists for EGDI based on SE, TOPSIS, and DEA, to guide nations to improve EG services toward achieving SDGs.

Table 1
List of Quantitative Evaluation Methods Related to EGDI.

Method	Reference (s)
Regression Analysis	Dias (2020), Abu-Shanab and Osmani (2019), Anwer, Esichaikul, Rehman, and Anjum (2016), Zhao, Shen, et al. (2014), Siau and Long (2009)
Correlation analysis	Yera et al. (2020), Lytras and Şerban (2020), Máchová et al. (2018), Máchová and Lněnička (2015)
Regression Analysis+Correlation Analysis	Perdał (2016), Zhao, Collier, and Deng (2014), Zhao (2013)
Correlation analysis+Structural Equation Modeling (SEM)	Whitmore (2012), Zhao, Wallis, and Singh (2015), Ali et al. (2018)
Standardization Method	Park and Oh (2018)
Cluster Analysis	Chen and Aklikokou (2019)
Analytical-Hierarch Process Analysis (AHP)	Choi et al. (2016), Hassan and Lee (2019)
Panel Data Analysis	Lee (2017)
Data Envelopment Analysis (DEA)	Choi and Park (2019)
Correlation Analysis+Cluster Analysis	Hatmanu et al. (2014)

2.2. Limitations of existing EGDI performance evaluation methods

Currently, the *Simple Additive Weighting* (SAW) method is used to produce EGDI scores. EGDI is a composite index based on the weighted average of three normalized indices, *namely,* TII, HCI, and OSI (UN-G, 2018). Each of these indices is a composite measure of differently extracted and independently analyzed indicators. The method constructs composite EGDI scores using the following three steps: i) selection of indices and associated indicators; ii) data weighting and aggregation procedure to derive EGDI scores; and iii) absolute ranking of countries based on the generated EGDI scores.

Notably, the SAW method has some strengths and weaknesses. Its popularity emerges from its transparency and simplicity of implementation. It helps policymakers and governments to determine the trends and levels of EG development. However, the SAW method is built on a flawed equal weighting assumption and does not go beyond the comparison of the scores to produce an absolute ranking of countries. The equal weighting assumption of the three EGDI sub-indices is based on an unrealistic substitution law, where a high score on one low-importance sub-index may compensate for a low score on another high-importance sub-index. Hence, the equal aggregation of the values may lead to information loss and human biased judgments (Büyüközkan & Karabulut, 2018; Zhou, Fan, & Zhou, 2010). Further, Wu, Fu, Shen, and Liu (2018) discussed the importance of the discrimination power of indices based on the usage of different weights in the domain of sustainable society index. Similarly, Becker, Saisana, Paruolo, and Vandecasteele (2017) discussed the necessity of using different weights and the importance of the selection of indicators when constructing their resource governance index, useful country index, and water retention index. They recommended the use of non-compensatory approaches to create sustainability indicators based on data-driven weights of indicators.

Another weakness of the SAW method is that it does not provide any empirical and thoughtful insights into the identification of the set of best-practice benchmark, other than the absolute ranking of countries. Further, neither does it generate efficiency and effectiveness indices nor recommends targets for improvement to help policymakers in developing and innovating EG developments.

The SAW method with equal weighting was applied to other indicators related to SDGs and reported similar limitations (Lafortune, Fuller, Moreno, Schmidt-Traub, & Kroll, 2018). Diaz-Sarachaga et al. (2018) elaborated further that a biased selection of indicators can favor specific countries. They also highlighted that the focus was on maximizing the performance on certain goals, which can be easily achieved by developed countries at the expense of inappropriate consumption of resources. Consequently, the creation of a more customized evaluation method to cater to regional needs is required.

3. Proposed hybrid methods for enhancing the evaluation of EGDI

In this section, we present our proposed methods to address the limitations discussed above, while using the same EGDI normalized data but processing them differently. These methods include SE (to generate data-driven weights), TOPSIS (to provide a relative ranking of countries instead of using absolute ranking methods), and DEA (to identify the best-practice benchmarking approach to recommend improvement targets and to introduce efficiency and effectiveness indices to assess progress toward achieving national goals).

Let us assume the existence of n countries whose EGDI scores are constructed using m indices. Let x_{ij} be the raw value to be standardized

Table 2
List of Hybrid Evaluation Methods Targeting Specific SDGs.

Methodologies	SDGs						
	Health (SDG 3)	Energy (SDG 7)	Industry (SDG 9)	Sustainable Cities (SDG 11)	Consumption (SDG 12)	Climate (SDG 13)	Land Life (SDG 15)
AHP, HFL-COPRAS[a] (Büyüközkan & Karabulut, 2018)		X					
AHP, TOPSIS (Guzmán-Sánchez, Jato-Espino, Lombillo, & Diaz-Sarachaga, 2018)				X			
AHP, Entropy (Zhao, Tan, Shen, Zhang, & Wang, 2019)		X					
AHP, Fuzzy Logic, TOPSIS (Jato-Espino, Indacoechea-Vega, Gáspár, & Castro-Fresno, 2018)				X			
AHP, Fuzzy Logic (Kacem et al., 2019)						X	X
Additive model, Regression, SVM (Marcillo-Delgado, Ortego, & Pérez-Foguet, 2019)		X					
DEA, Entropy, Regression (Gao, Wang, Zhang, & Wei, 2019)					X		
DEA, Regression (Ibrahim, Daneshvar, Hocaoğlu, & Oluseye, 2019)	X						
Entropy, QUALIFLEX[b], VIKOR (Liang, Zhao, & Hong, 2018)					X		
PCA[c], VAR (Mamipour, Yahoo, & Jalalvandi, 2019)	X						
PCA, Regression, Cluster Analysis (Megyesiova & Lieskovska, 2018)	X						
PCA, Regression (Oyekale, 2017)	X						
Factor Analysis, SEM (Park & Lee, 2018)							X
Factor Analysis, Reduced Equation Model (Ricciardelli, Manfredi, & Antonicelli, 2018)				X			
Factor analysis, Super-efficiency DEA (Xing, Xue, & Wang, 2018)						X	
TOPSIS, VIKOR[d], GRA[e] (Bhatia, Dora, & Jakhar, 2019)			X				

[a] **HFL-COPRAS -** Hesitant fuzzy linguistic complex proportional assessment
[b] **QUALIFLEX** - Qualitative flexible
[c] **PCA** - Principle component analysis
[d] **VIKOR** - VlseKriterijuska Optimizacija Komoromisno Resenje
[e] **GRA** - Grey relation analysis

for each country i for $i = 1, \ldots, n$ with respect to index j for $j = 1, \ldots, m$. Further, let X_{ij} be its corresponding standardized value (or Z-score) and w_j be the weight of index j. For each index j and $j = 1, \ldots, m$, let max_j and min_j be the maximum and minimum of x_{ij} values, respectively and let $\sigma_j = (max_j - min_j)$ be the corresponding standard deviation of x_{ij}values over all countries for $i = 1, \ldots, n$.

The standardization and normalization procedure involves two steps. The standardization step assures that all indices are transformed into the same type, either into the maximization of benefit type (i.e., the larger, the better) or minimization of cost type (i.e., the smaller, the better). The normalization step assures that all standardized values fall in the interval [0, 1]. The standardized X_{ij} values of raw x_{ij} of benefit or cost types are computed using one of the following transformation equations:

$$X_{ij} = (x_{ij} - min_j)/\ \sigma_j, \text{ for the benefit maximization type}$$
$$X_{ij} = (max_j - x_{ij})/\ \sigma_j, \text{ for the cost minimization type}$$

3.1. Current UN method to evaluate EGDI: SAW

The SAW is used to evaluate EGDI and is explained below:

i) *Selection of Indices and Associated Indicators*

According to the UN E-government survey (UN-G, 2018), three essential indices with associated indicators on EG status are selected, namely, (a) TII, which measures the adequacy or the state of the development of telecommunication infrastructure, (b) HCI, which measures the ability of human resources to promote and use of ICT, or the inherent human capital, and (c) OSI, which measures the availability, content, scope, and quality of online services.

(a) **TII** consists of five indicators: (i) estimated *Internet users* per 100 inhabitants (measured as a percentage of population); (ii) percentage of people with primary *fixed telephone lines* subscription; (iii) percentage of population with *mobile phone subscriptions*; (iv) percentage of people with *active mobile broadband subscriptions*; and (v) percentage of population with *fixed wired broadband subscriptions*. Each of the five indicators is normalized using the Z_{score} procedure to derive its Z_{score} value. The TZ_{score} value for each country is computed as the average of the five Z_{score} values as follows:

$$\boldsymbol{TZ_{score}} = 1/5 \times \{Internet\ \ user\ \ Z_{score} + fixed\ \ telephone\ \ subscription\ \ Z_{score} + mobile\ \ telephone\ \ subscription\ \ Z_{score} + active\ \ mobile\ \ broadband\ \ subscription\ \ Z_{score} + wired\ \ broadband\ \ subscription\ \ Z_{score}\} \quad (1)$$

(b) **HCI** consists of four indicators, namely: (i) adult literacy rate; (ii) the combined primary, secondary, and tertiary gross enrollment ratio; (iii) estimated years of schooling; and (iv) mean years of education. Similar to the calculation of TZ_{score} value, using the Z_{score} values for each of the four standardized indicators, the **HCI** value (HZ_{score}) for each country is computed as follows:

$$\boldsymbol{HZ_{score}} = 1/3 \times (\text{adult literacy rate } Z_{score}) + 2/9 \times (\text{gross enrollment ratio } Z_{score}) + 2/9 \times (\text{estimated years of schooling } Z_{score}) + 2/9 \times (\text{mean years of schooling } Z_{score}) \quad (2)$$

(c) **OSI** is a composite normalized score based on an online service questionnaire (OSQ) survey and a member state questionnaire survey. The UN 2018 survey comprises a list of 140 questions, which call for a binary response. Every positive answer generates a "more in-depth question" inside and across the patterns. The OSI assesses the four stages of EG development, namely,

emerging information services, enhanced information services, transactional services, and connected services. In addition to evaluating the development of EG portals, the OSQ survey includes questions related to the critical SD of EG, for example, open government data, e-participation, mobile-government, and whole-of-government approach. The complete review of OSQ further includes questions (or proxy themes) related to key outcome services that spread across the domains of SDGs.

OZ_{score} is presented in a normalized value in the interval [0, 1]. It is defined to take the value of the ratio of the actual total score of a country less the lowest total score divided by the standard deviation of the total score values over all countries.

ii) *Data Weighting and Aggregation to Derive EGDI Scores*

The EGDI assumes that all three indices are of the benefit type. The EGDI $Z_{score}(i)$ for each country (i) is computed using the arithmetic mean of the three individual Z_{score}values for the TII, HCI, and OSI indices as follows:

$$Z_{score}(i) = 1/3 \times \{TZ_{score}(i) + HZ_{score}(i) + OZ_{score}(i)\} \quad \forall \quad i = 1, \ldots, n \tag{3}$$

iii) *Absolute Ranking Countries Based on the Generated EGDI Scores*

The Z_{score} values are ranked in decreasing order of their values to produce an EGDI ranking of countries from the best to the worst performers. The Z_{score} values are also used to provide some simple descriptive measures and reported by regions and different income groups.

3.2 Weight. determination using SE

The entropy of information loss was proposed by Shannon (1948) to deal with the accuracy of the transformation of information messages in a system. SE measures the degree of information loss (information disorder or information effectiveness) in terms of the probability of randomness. SE has been used as a weighting method to determine the data-driven weights of an index based on the amount of variation among the index values. Hence, it avoids the subjectivity bias of decision-makers that exist in other multi-criteria approaches, such as AHP. Mahmoudi, Emrouznejad, Khosroshahi, Khashei, and Rajabi (2019) used SE, TOPSIS, and DEA to evaluate the performance of thermal power plants. Further, Suh et al. (2019) reported that the elimination of human bias would yield more realistic results and used SE to derive data-driven weights for evaluating the performance of mobile services.

Given the existence of (n) countries, and (m) evaluation indices with a decision matrix, $D = [X_{ij}]$, $\forall i = 1, \cdots, n$, $\forall j = 1, \cdots, m$. The steps of the SE method for the determination of data-driven weights are then explained as follows.

Step 1: *Linear normalization to compute the probability of surprise in the data*

$$p_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \quad \forall i = 1, \cdots, n \quad \& \quad \forall j = 1, \cdots, m \tag{4}$$

Step 2: *Computation of SE for each index*

$$e_j = -\frac{1}{Ln(n)} \times \sum_{i=1}^{n} p_{ij} \times Ln(p_{ij}) \qquad \forall j = 1, \cdots, m \tag{5}$$

When $p_{ij} = 0$, *then* $p_{ij} \times Ln\left(p_{ij}\right) = 0$

Step 3: *Computation of the disorder and weight for each index*

$$d_j = 1 - e_j \quad \& \quad w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \quad \forall j = 1, \cdots, m \tag{6}$$

It can be seen from (6) when the disorder (d_j) is large, this indicates a significant difference among values on a given index (j), and the entropy (e_j) would be small. Consequently, the weight would be substantial to indicate that the index is critical and provides more useful information.

3.3. Relative ranking of countries based on distance from virtual best and worst using TOPSIS

TOPSIS was introduced by Hwang and Yoon (1981) as a multi-attribute decision-making method to rank alternative entities by calculating the closeness of each entity to BIS and WIS. The BIS is defined as the *virtual* entity constructed using the best value on each index. The WIS is the virtual entity similarly built using the worst value on each measure. TOPSIS would simultaneously select the top-ranked entity which has the shortest distance to BIS and the farthest distance from WIS.

Given the existence of n countries (entities), and m indices, and a decision matrix $D = [X_{ij}]$ $\forall i = 1, \cdots, n$ & $\forall j = 1, \cdots, m$, with standardized values of benefit type (say the larger, the better), then TOPSIS steps are explained as follows:

Step 1: *Standardization of values to obtain a normalized decision matrix R*

$$R = [r_{ij}] \quad where \quad r_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}^2} \quad \forall i = 1, \cdots, n \quad \& \quad \forall j = 1, \cdots, m \tag{7}$$

Step 2: *Computation of the weighted normalized matrix V using SE*

$$V = [v_{ij}] \quad where \quad v_{ij} = w_j \times r_{ij} \quad \forall i = 1, \cdots, n \quad \& \quad \forall j = 1, \cdots, m \tag{8}$$

where w_j is the weight of index j as computed in Section 3.2

Step 3: *Determination of* BIS *and* WIS

$$BIS = \left(v_1^+, \cdots v_j^+ \cdots, v_m^+\right), \quad \text{where} \quad v_j^+ = Max\{v_{ij}\} \quad \forall i = 1, \cdots, n \tag{9}$$

$$WIS = \left(v_1^-, \cdots v_j^- \cdots, v_m^-\right) \quad \text{where} \quad v_j^- = Min\{v_{ij}\} \quad \forall i = 1, \cdots, n \tag{10}$$

Step 4: *Calculation of the distances of each entity from BIS and WIS*

$$d_i^+ = \left(\sqrt{2\sum_{j=1}^{m}(v_{ij} - v_j^+)^2}\right) \quad \forall i = 1, \cdots, n \tag{11}$$

$$d_i^- = \left(\sqrt{2\sum_{j=1}^{m}(v_{ij} - v_j^-)^2}\right) \quad \forall i = 1, \cdots, n \tag{12}$$

Step 5: *Calculation of the relative closeness*

$$C_i = \frac{d_i^-}{d_i^- + d_i^+} \quad 0 < C_i < 1, \qquad \forall i = 1, \cdots, n \tag{13}$$

Step 6: *Ranking of alternative countries*

The countries are ranked from the best to the worst based on the decreasing order of their C_i closeness values, that is, the top rank is assigned a position of (1) to the country with the highest closeness value, and the last rank (n) is designated to the country with the lowest closeness value.

Note that the power of TOPSIS is limited to its relative ranking approach. Besides, it can be implemented without weight by merely removing Step 2. Further, note that, if the decision matrix D is standardized to a cost type (i.e., the lower, the better), then in Step 3, v_j^+ should be computed in the same spirit as the $Min\{v_{ij}\}$ values, and v_j^-should be computed as the $Max\{v_{ij}\}$ values. TOPSIS has been hybridized with other methods, including entropy to evaluate public Blockchain (Tang, Shi, & Dong, 2019) and AHP to assess the sustainability of quality

service in long-term care programs (Song, Sun, Li, & Que, 2016).

3.4. Generating benchmarked efficiency and effectiveness measures using DEA

DEA is a nonparametric linear programming approach, which evaluates the relative performance of a set of decision-making units (DMUs or countries). Each DMU utilizes multiple inputs that are transformed into various outputs. DEA generates a relative performance score for each DMU by measuring the quality of its transformation compared to its peers. The DEA performance score is defined by the transformation efficiency ratio as the sum of the total weighted outputs over the sum of the total weighted inputs. The weights for the inputs and outputs are not fixed to pre-defined values, as in the SAW method, but are variable values that are optimized in the best interest of the DMU being evaluated, subject to relativity constraints. The relativity constraints indicate that the performance ratio of any DMU should not exceed one. A DMU with a DEA score of one is called efficient, whereas a DMU with a score of less than one is called inefficient.

In the literature, two basic DEA models exist. First, a DEA model that assumes all DMUs operate under the homogeneity assumption of constant returns to scale (DEA-CRS; Charnes et al., 1978). According to Dyson et al. (2001), non-homogeneity of DMUs originates from different environments and economies of scale. In the context of e-government services, the countries are heterogeneous because of differences in Internet speeds and ICT regulations (i.e., environment), people's knowledge and skills (i.e., human capital), and e-services maturity levels (i.e., technical differences). To address the heterogeneity issue in EG and SDG contexts, a second model, the variable returns to scale (DEA-VRS) was proposed to accommodate the scale effects in the performance analysis (Banker, Charnes, & Cooper, 1984). The relationship between the DEA-CRS (known as primal) and the DEA-VRS (known as dual or envelopment) models are discussed.

We present below an overview of the DEA-CRS model to explicitly define the essential indicators of the transformation efficiency ratio and associated constraints. These necessary indicators will be used to introduce our newly proposed efficiency and effectiveness indices. The aim is to generate more evidence-based insights for better-informed decisions. We achieve this objective by splitting the transformation efficiency ratio into an *input-efficiency* measure on the efficiency of utilization of input resources and an *output-effectiveness* measure on the effectiveness of the generated outputs.

The DEA-CRS model can be sub-divided into *input-oriented* and *output-oriented* DEA models. The output-oriented model maximizes the sum of the total weighted outputs to generate an *output-effectiveness* performance score for each DMU. A DMU with an output-oriented performance score of one is called *effective,* whereas a DMU with a score of less than one is deemed *ineffective.* DEA establishes the set of the best-practice effective benchmark to recommend *output targets* to increase the level of outputs for each ineffective DMU to become effective at the given fixed level of inputs. By contrast, the input-orientation model minimizes the sum of the total weighted inputs to generate an *input-efficiency* performance score for each DMU. A DMU with an input-oriented performance score of one is called *efficient,* whereas a DMU with a score of less than one is deemed *inefficient.* DEA similarly recommends *input targets* to reduce the level of inputs for each DMU to become efficient at the given fixed levels of outputs.

Table 3 provides linear programming formulations for the input-oriented (DEA-CRS-I) and output-oriented (DEA-CRS-O) models under CRS assumptions. For each DMU/country ($i = 1,\ldots,n$) in a set of homogenous DMUs for evaluation, r represents the number of input variables, s represents the number of output variables, and x_{ij} and y_{ik} denote the amount of input j utilized and the amount of output k generated by a DMU (i) respectively; $u_j$and $v_k$represent the weights assigned to input j and output k, respectively. The quality value of the transformation for a DMU (i) is obtained by maximizing a non-linear objective performance function. The function is expressed by the production/transformation efficiency ratio ($\sum_{k=1}^{s} v_k y_{ik} / \sum_{j=1}^{m} u_j x_{ij}$), subject to no production efficiency ratios exceeding one. The ratio is linearized in two different ways to generate the two input and output-oriented linear models to solve them optimally. In the DEA output-oriented model (DEA-CRS-O), the denominator of the non-linear objective is set to one, whereas in the input-oriented model (DEA-CRS-I), the numerator is set to one.

Table 3
DEA Output-oriented and Input-oriented Constant Returns to Scale Models (primal).

DEA-CRS-O: Output-oriented constant returns to scale model (Primal)	**DEA-CRS-I**: Input-oriented constant returns to scale model (Primal)
Maximize $\theta_p = \sum_{k=1}^{s} v_k y_{pk}$	Minimize $\varphi_p = \sum_{j=1}^{r} u_j x_{pj}$
Subject to:	Subject to:
$\sum_{j=1}^{r} u_j x_{pj} = 1$	$\sum_{k=1}^{s} v_k y_{pk} = 1$
$\sum_{k=1}^{s} v_k y_{ik} - \sum_{j=1}^{r} u_j x_{ij} \le 0; \quad \forall i = 1,\cdots,n$	$\sum_{k=1}^{s} v_k y_{ik} - \sum_{j=1}^{r} u_j x_{ij} \le 0; \quad \forall i = 1,\cdots,n$
u_j *and* $v_k \ge 0; \quad \forall k = 1,\cdots,s; \quad \forall j = 1,\cdots, r$	u_j *and* $v_k \ge 0; \quad \forall k = 1,\cdots,s; \quad \forall j = 1,\cdots, r$

In both primal DEA-CRS models, the first constraint expresses the linearization type, whereas the second set of n constraints imposes the relativity concept that no ratio for any DMU should be more than one. The value of the objective (φ_p) determines the *input-efficiency* score from solving the DEA-CRS-I model, whereas θ_p determines the *output-effectiveness* score from solving the DEA-CRS-O model for any DMU (p). Both φ_p and θ_p have equal values under the DEA-CRS-I and DEA-CRS-O models. However, they have different values under DEA-VRS-I and DEA-VRS-O dual models due to the returns to scale effects. A discussion on the relationship between VRS and CRS efficiencies can be found in Cooper, Seiford, and Tone (2006). Each of the DEA models needs to be executed as many times as the number of available DMUs to derive the DEA input-efficiency and output-effectiveness performance scores for each DMU.

The DEA-VRS dual models are often adopted to model the effect of heterogeneity assumption (Banker et al., 1984). They are derived using the duality theory of linear programming of the DEA-CRS primal model with the addition of a new constraint ($\sum_{j=1}^{n} \lambda_i = 1$), where ($\lambda_i$)s represent the dual variables of the constraints in the linear programming primal model associated with DMU (i). Table 4 presents the linear programming formulations for the input-oriented (DEA-VRS-I) and the output-oriented (DEA-VRS-O) dual (envelopment) models under variable returns to scale. The derivation of the input-efficiency and output-effectiveness scores for each DMU was successfully implemented to evaluate the satisfaction of citizens/DMUs to assess the quality of provision of EG services (Osman et al., 2019). DEA models have been applied effectively in different contexts, ranging from financial and banking applications (Holod & Lewis, 2011; Sufian & Kamarudin, 2014) to power plant management and big data analytics (Khezrimotlagh, Zhu, Cook, & Toloo, 2019). For a comprehensive review of DEA applications and theory, we refer to the book by Osman, Anouze, and Emrouznejad (2014).

Table 4
DEA Input-oriented and Output Variable Returns to Scale Models (Dual).

DEA-VRS-I: *DEA input-oriented variable returns to scale model (Dual)*	**DEA-VRS-O**: *output-oriented variable returns to scale model (Dual)*
Minimize θ_p	Maximize φ_p
Subject to:	Subject to:
$\sum_{i=1}^{n} \lambda_i x_{ij} \le \theta_p x_{pj} \quad ; \forall j = 1,\cdots,s$	$\sum_{i=1}^{n} \lambda_i x_{ij} \le x_{pj} \quad ; \forall j = 1,\cdots,m$
$\sum_{i=1}^{n} \lambda_i y_{ir} \ge y_{pr} \quad ; \forall r = 1,\cdots,m$	$\sum_{i=1}^{n} \lambda_i y_{ir} \ge \varphi_p y_{pr} \quad ; \forall r = 1,\cdots,s$
$\sum_{i=1}^{n} \lambda_j = 1$	$\sum_{j=1}^{n} \lambda_j = 1$
$\lambda_i \ge 0; \quad \forall i = 1,\cdots,n; \theta_p$ free	$\lambda_i \ge 0 \quad \forall i = 1,\cdots,n; \varphi_p$ free

One of the essential steps in the DEA modeling and implementation process is the definition of DMUs and associated input and output variables. In this study, we use a set of countries to define the set of DMUs. The associated set of inputs and outputs are linked to the EG's SDGs. In our approach, the collection of n = 193 countries is used as a set of DMUs. As the OSI measures the essential outcome of EG services that are spread across domains of SDGs, it is considered as a single output variable. By contrast, the TII measures the adequacy of ICT infrastructure, and the HCI measures the ability of human resources to promote and use ICTs. Hence, we use them in the model as the set of two input variables. The TII and HCI are similarly used as input enabler variables when developing a global innovation index based on a fuzzy set qualitative comparative analysis in Crespo and Crespo (2016). The DEA SolverPro Software Version 6 by SAITECH is used to generate the DEA results (Cooper et al., 2006).

4. Empirical results and analytics findings

This section reports our empirical results to highlight analytics findings and recommends target improvements to generate data analytics insights to enhance the outcomes and impact of SDGs in general and EGDI in particular. We obtain the empirical results from the combination of the three primary methods presented in Section 3. The hybrid combination enables us to gradually observe how each method enhanced our results, with a potential explanation of the introduced benefits. The following hybrid methods were implemented:

H1) SAW: The SAW method using equal weights to aggregate indices;

H2) SAW+SE: The SAW method using the SE weights;

H3) SAW+TOPSIS: The SAW method using the relative ranking of TOPSIS instead of the absolute ranking of SAW;

H4) SAW+SE+TOPSIS: The SAW–SE hybrid using the relative ranking of TOPSIS;

H5) DEA-O: The data envelopment analysis with a variable returns to scale model to produce output-oriented effectiveness scores and benchmarking results;

H6) DEA-I: The data envelopment analysis with a variable returns to scale model to produce input-oriented efficiency scores and benchmarking results; and

H7) DEA+SE+TOPSIS: This implementation is similar to H4 and combines H5 and H6 to create a single performance weighted score based on efficiency and effectiveness scores.

4.1. Data sources

We utilized EGDI data for the last three periods (2014, 2016, and 2018) that are available online on the UN E-Government Knowledge portal and published in the biennial UN EG surveys (UN-EGK, 2018). The UN-DESA collects the data from three sources. The International Telecommunications Union provides the data for TII; the UN Educational, Scientific, and Cultural Organization provides the HCI data; the UN-DESA delivers the OSI data using an independent OSQ and member state questionnaire survey to assess the national online EG presence and the SDG impact since 2001. The questionnaire involves all 193 UN member states (countries). The EGDI dataset used and the results are published online (Osman & Zablith, 2020).

4.2. SE weights for indicators and impact over time

Experts may subjectively determine the weights of indicators based on their importance. However, reaching an agreement among experts is challenging. This disagreement led to the adoption of an equal weighting approach for the SDG indices (Lafortune et al., 2018). Consequently, the conflict led to a lack of guidance on how to improve the level of innovation and prioritization of managerial actions on SDGs by decision-makers across countries (Crespo & Crespo, 2016). Using the SE method has enabled us to derive data-driven weights objectively to determine the importance of the EGDI.

Fig. 1 shows the change in weights for each index over the three periods and how they move in different directions. For instance, the SE weights for *HCI* started at a low value of less than 0.10 in 2014 and increased gradually over the last two periods to reach a maximum value of 0.1377 (i.e., 37.7% increase). The small change reflects the marginal impact of HCI on the development of EG activities, and consequently, on SDGs. Examining the SE weights for TII, it increased from 0.45 in 2014 to 0.50 in 2018 (i.e., 11.11% increase). It is the most important and impactful among the EGDI, indicating that many variations exist in ICT development across countries. However, observing the weights of the *OSI*, one can notice a decreasing trend, from 0.45 to 0.35 (i.e., 22.22% decrease). The OSI trend indicates that SDG activities have not changed much worldwide, rather, they have even declined over the last three periods. The decrease in OSI weight is probably due to the less variability of OSI values among countries, that is, countries have less variability leading to smaller OSI values. Further, this feature indicates that most nations have reached the same homogenous level of achievements on the embedded services. The homogeneity explanation leads to the conclusion that the aggregation method to derive the OSI value from its sub-indicators does not allow for enough differentiation among countries, and the associated variable measures for the sub-indicators should be reported individually.

Finally, despite the differences in the trend values of EGDI, the SAW method based on equal weights of indices generates a compensated substitution effect. As shown in the first column of Fig. 2, the overall EGDI values follow an increasing trend, from an average of 0.47 in 2014 to 0.49 in 2016 and 0.54 in 2018. However, the introduction of SE into SAW in H2 (SAW+SE) further adjusts the averages down to 0.40, 0.44, and 0.50 in Column 2 of Fig. 2, but still, hide the individual importance and trend of each sub-index of EGDI.

4.3. Impact of change in weights on the ranking of countries

We demonstrate the impact of the weights and degree of changes in the ranking of countries using the various results generated from the seven hybrid implementations (H1,…, H7). Table 5 presents the results for each hybrid method, the maximum (Max Upward) and minimum (Min Downward) changes in rankings, followed by the percentage of nations that changed rank (% Difference), the standard deviation of differences (Standard Deviation), and the top four countries with their abbreviated names and their EGDI scores. Table 5 surprisingly shows that more than 91%, 92%, and 91% of countries changed their ranks over 2014, 2016, 2018, respectively under the H2 method, and increasing to 98% under the H7 method. The maximum upward and downward changes in ranks were also substantial, ranging from −74 up to 84 points, respectively. It is worth noting that the change in ranking does not reflect the EG development across countries, which has impacted the change annually. Furthermore, the SAW method does not tell what has changed across countries, but mainly reflects an absolute impact of the race toward a higher ranking. Achieving this may require additional data analysis at the sub-index level, which is not possible because of non-availability of disaggregated or granular data.

To illustrate, Fig. 3 compares the number of changes in the ranks of countries and depicts them on histograms annually over the three periods for the H2 (SAW+SE) method. The differences in each period follow a normal-shape distribution and each distribution has different means and standard deviations of changes in ranks. For instance, the mean was zero, and the standard deviations narrowed over the period, starting at 8.59, through 6.68 down to 5.49 for 2014, 2016, and 2018, respectively.

For more illustration, Fig. 4 shows the degree of changes in ranks for the list of high-income countries for 2018. Although ranks of countries such as Portugal and the US were not affected, that of the United Arab Emirates (AE) increased by 14 places, whereas Palau's dropped by 10 places. The changes in the first and second-ranked countries resulting

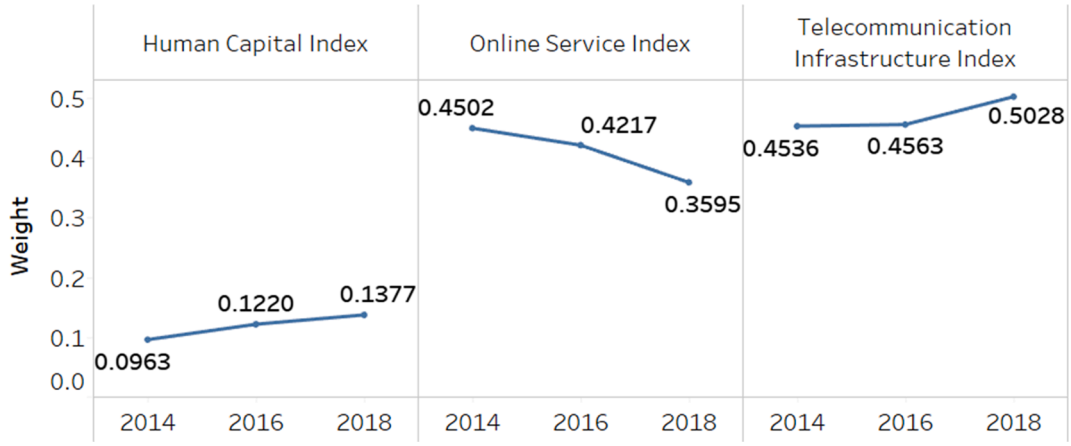

Fig. 1. Change in SE Data-Driven Weights of Indices Over the Three Years.

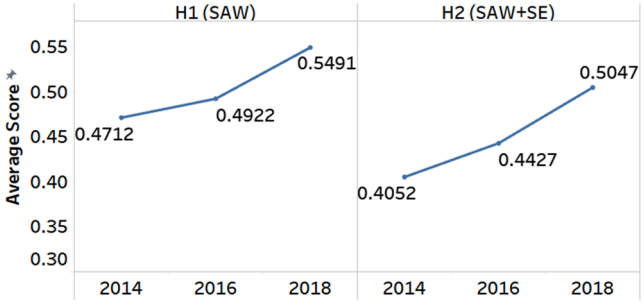

Fig. 2. Impact of Weights on SAW.

from the impact of weight changes were analyzed. It was interesting to observe that Denmark (DK) was ranked first in the H1 (SAW) method, but lost its position to become second, behind the Republic of Korea (KR), which improved its rank by two positions.

To provide more insights into the changes in ranks, Table 6 presents an illustration of the results for DK and the KR. DK has a better OZ_{score} value (1) for OSI and HZ_{score} value (0.947) for HCI but a lower TZ_{score} value (0.797) for TII than those of the KR. As TII has a higher SE weight, the SAW+SE scores changed to 0.891 and 0.899 for DK and the KR, respectively. The change in the weighted average of Z_{score} (SAW+SE) helped move the KR to the first position. This example illustrates the sensitivity of ranks to the change in weights. Consequently, if the UN's interest is not to report the impact of racing among countries toward achieving a higher rank, deeper thinking on how to derive weights is required. The choice of weights should either reflect the real development on an index or indicate the best interest of a country being evaluated for greater motivation and alignment on SDGs.

Table 5
Impact of SE Weights and Degree of Changes on the Ranking of Countries.

		H1 (SAW)	H2 (SAW+SE)	H3 ((SAW+TOPSIS)	H4 (SAW+SE+TOPSIS)	H5 (DEA-O)	H6 (DEA-I)	H7 (DEA+SE+TOPSIS)
2014	Max Upward Rank	–	ET (+30)	ET (+30)	BF (+38)	ET (+84)	LY (+48)	TG (+70)
	Min Downward Rank	–	KP (−29)	MH (−15)	KP (−34)	BB (−74)	MA (−54)	GT (−50)
	% Difference (Ranking)	–	91%	89%	95%	97%	96%	95%
	St. Deviation (Ranking)	–	8.59	5.96	10.59	25.30	16.93	18.00
	1st Country	KR (0.946)	KR (0.952)	KR (0.946)	KR (0.948)	KR (1)	KR (1)	KR (1)
	2nd Country	AU (0.910)	SG (0.927)	SG (0.904)	SG (0.910)	SG (1)	SG (1)	SG (1)
	3rd Country	SG (0.907)	FR (0.898)	JP (0.884)	JP (0.886)	FR-NZ (1)	FR-NZ (1)	AU (1)
	4th Country	FR (0.893)	JP (0.896)	GB (0.869)	GB (0.870)	AU-MC (1)	AU-MC (1)	JP (0.937)
2016	Max Upward Rank	–	AF (+18)	AG (+19)	ML (+31)	ET (+75)	PW (+57)	CF (+51)
	Min Downward Rank	–	KP (−31)	MN (−16)	KP (−35)	SM (−63)	BD (−40)	PK (−30)
	% Difference (Ranking)	–	92%	88%	93%	96%	96%	97%
	St. Deviation (Ranking)	–	6.68	6.53	10.33	23.09	15.14	15.47
	1st Country	GB (0.919)	GB (0.909)	KR (0.875)	KR (0.872)	KR (1)	KR (1)	KR (1)
	2nd Country	AU (0.914)	SG (0.895)	SG (0.865)	SG (0.866)	SG (1)	SG (1)	SG (1)
	3rd Country	KR (0.891)	KR (0.893)	GB (0.860)	GB (0.849)	GB (1)	GB (1)	GB (1)
	4th Country	SG (0.882)	AU (0.883)	JP (0.840)	JP (0.839)	AU-MC (1)	AU-MC (1)	AU-MC (1)
2018	Max Upward Rank	–	BF (+16)	SM (+24)	SM (+36)	IN (+83)	SM (+40)	KP (+57)
	Min Downward Rank	–	CU (−19)	CU (−19)	CU (−31)	SM (−57)	BD (−37)	SN (−31)
	% Difference (Ranking)	–	91%	93%	97%	98%	97%	98%
	St. Deviation (Ranking)	–	5.49	8.09	12.61	22.63	14.66	16.25
	1st Country	DK (0.915)	KR (0.899)	KR (0.871)	MC (0.868)	MC (1)	MC (1)	MC (1)
	2nd Country	AU (0.905)	DK (0.891)	JP (0.858)	KR (0.862)	KR (1)	KR (1)	KR (1)
	3rd Country	KR (0.901)	GB (0.881)	CH (0.847)	AE (0.862)	DK (1)	DK (1)	DK (1)
	4th Country	GB (0.899)	JP (0.880)	DK (0.842)	JP (0.852)	IS-AU (1)	IS-AU (1)	IS-AU (1)

Abbreviations: AE: United Arab Emirates; AF: Afghanistan; AG: Antigua and Barbuda; AU: Australia; BB: Barbados; BD: Bangladesh; BF: Burkina Faso; CF: Central Africa; CH: Switzerland; CU: Cuba; DK: Denmark; ET: Ethiopia; FR: France; GB: United Kingdom; GT: Guatemala; IN: India; IS: Iceland; JP: Japan; KP: Democratic People's Republic of Korea; KR: Republic of Korea; LY: Libya; MA: Morocco; MC: Monaco; MH: Marshall Islands; MN: Mongolia; ML: Mali; NZ: New Zealand; PK: Pakistan; PW: Palau; SG: Singapore; SM: San Marino; SN: Senegal; TG: Togo.

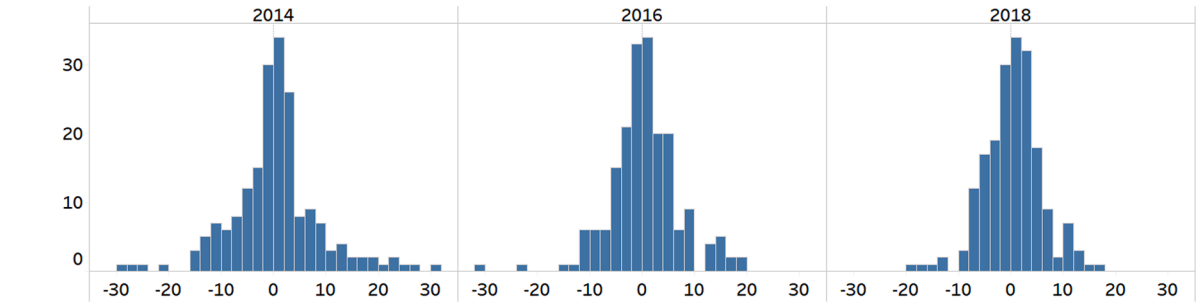

Fig. 3. Histograms of Change in Ranks Over the Three Years for H2 (SAW+SE).

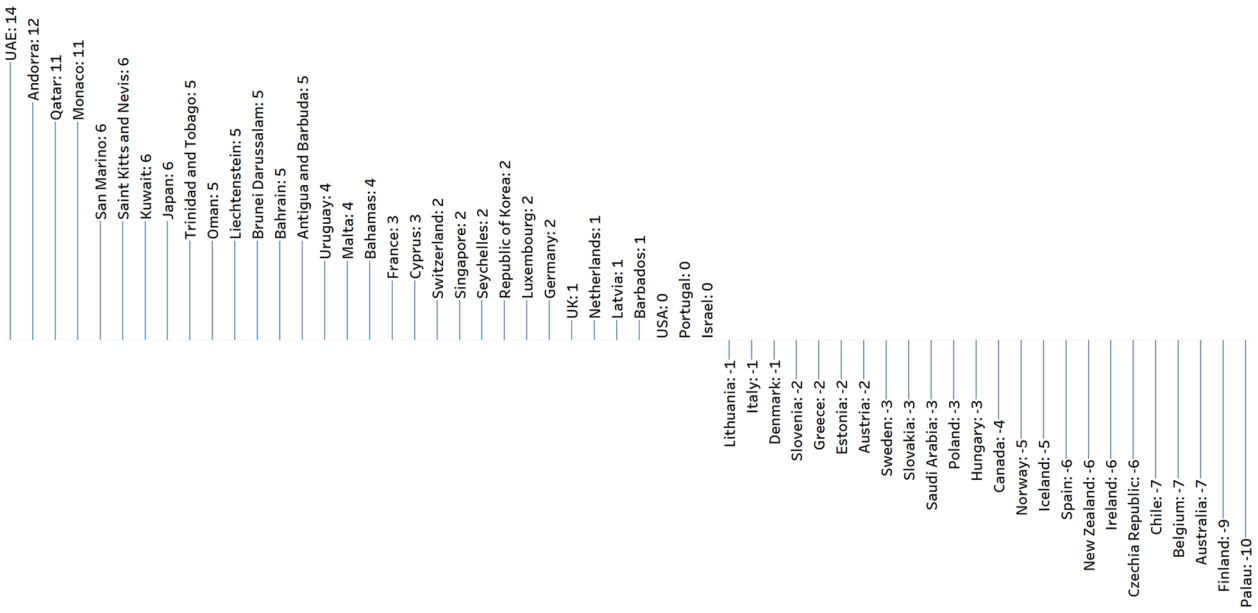

Fig. 4. Changes in Ranks of High-Income Countries for H2 (SAW+SE) in 2018.

4.4. TOPSIS impact on rankings based on deviations from best and worst countries

The introduction of different SE weights does not eliminate the substitution effect among indices. A country can reach a higher rank by focusing on improving the Z_{score}value of the highest weighted index, while missing the opportunity to enhance other SDG indices. The H1 (SAW) and H2 (SAW+SE) methods use an absolute ranking approach based on Z_{score} values, but they do not consider the deviations of an individual score from the overall best and worst Z_{score} values. TOPSIS aims to generate a well-rounded relative measure of performance for countries to derive relative ranks. The generated measures can further suggest guidance on how to improve, by comparing with the virtual best and worst ideal performers. Specifically, TOPSIS measures the relative distance deviations of a country's performance from the two virtual best and worst performers. Therefore, targets for improvements can be estimated based on the computed deviations from such ideals. Table 5 provides the percentage of countries and the extreme changes in ranks as well as the positions of the top nations for hybrids of SAW with TOPSIS in H3 and SAW with SE and TOPSIS in H4. The maximum changes are in H4 compared to H2 and H3 because of the introduction of distances from the virtual best and worst countries in the case of H2 and the integration of SE weights in the case of H3. Fig. 5 shows the impact of TOPSIS on SAW and weighted SAW, reflecting an increasing trend over the years.

To investigate the change in ranks due to TOPSIS distances from ideals between DK and the KR under H1 (SAW) and H3 (SAW+TOPSIS), Table 7 provides the calculation of the distances from the worst and best virtual ideal countries for the SAW and TOPSIS+SAW scores for 2018. The data for KR shows that it has a shorter distance to the ideal best (d_i^+ = 0.00122) and a longer distance from the worst (d_i^- = 0.00819) compared to the values of DK. The distances led to a higher H3 (TOPSIS)

Table 6
Impact of SE Weights on the Changes in Ranks for DK and KR in 2018.

Country	HCI HZ_{score} SE Weight (0.137)	OSI OZ_{score} SE Weight (0.359)	TIITZ_{score} SE Weight (0.502)	H1Z_{score} (SAW)	H2 Z_{score} (SAW+SE)
DK	0.947	1	0.797	**0.915**	0.891
KR	0.874	0.979	0.849	0.901	**0.899**

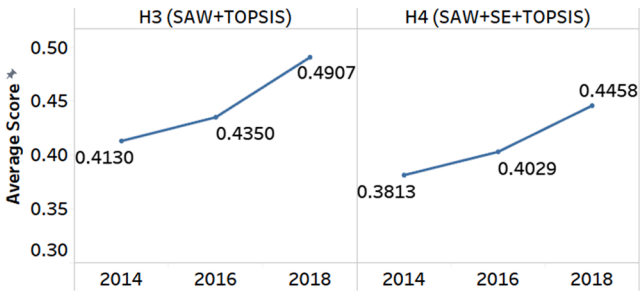

Fig. 5. Impact of TOPSIS on SAW and Weighted SAW (SAW+SE).

Table 7
Distances from Worst and Ideal Virtual Points for DK and KR.

Country	Distance to Ideal (d_i^+)	Distance to Worst (d_i^-)	Total $d_i^+ + d_i^-$	H1 Score (SAW)	H3 Score (SAW+TOPSIS)
DK	0.00153	0.00819	0.00972	**0.915**	0.84197
KR	0.00122	0.00833	0.00955	0.901	**0.87169**

score for KR (0.87169) than that for DK (0.84197), and consequently, a better rank for KR under H3, whereas KR ranked behind DK under the H1 (SAW) method. Further, if one introduces the SE weight into H3 (SAW+TOPSIS)—the combined results are shown under H4 (SAW+SE+TOPSIS) in Table 5—the weighted score would put KR second to Monaco, which was ranked first in 2018 for similar reasons.

4.5. Efficiency and effectiveness indices and benchmarking analyses

To better support nations in advancing sustainability toward achieving SDGs, we propose assessing the performance of a country based on an efficiency index—to measure the utilization of resources—and an effectiveness index—to measure the generated outputs and outcomes. Two DEA models are implemented to measure the efficiency and effectiveness scores: H5 (DEA_I) and H6 (DEA_O) variable returns to scale models. Results from the H5 and H6 methods are provided in Fig. 6 in terms of the averages of efficiency and effectiveness scores for all countries over the last three-year evaluation periods. Further, the impact on the changes in the ranks of nations and other measures under H5 (DEA-O) for effectiveness and H6 (DEA-I) for the efficiency scores are provided in Table 5. We highlight several observations from the DEA results. First, under both DEA-I and DEA-O implementations, ranks of more than 95% of countries changed, the most significant changes among all the methods. Second, the results from both DEA models are robust as they produced the same country names for the first (Monaco) and second (KR) ranks as compared to those named by H4 (SAW+SE+TOPSIS) for all the periods. Third, the overall average of efficiency scores of H7 (DEA+SE+TOPSIS) is lower than the average of effectiveness scores over the three years, as shown in Fig. 6. Both performance efficiency and effectiveness measures follow an increasing order but at different rates. The averages of the DEA-I input-efficiency score indicate that countries are less efficient and more effective, they should focus more on improving utilization of their input resources (TII) and (HCI) scores if they cannot increase the current level of outputs (OSI). This insight will either guide countries to become more efficient or focus on improving the OSI outcomes if they cannot reduce the input resources.

Last, the DEA input-efficiency scores of H5 and the DEA output-effectiveness scores of H6 are aggregated using SE to create a single index on the transformation efficiency as H7 (DEA+SE+TOPSIS) and are presented in Fig. 6. An interesting observation is that the averages of the transformation efficiency scores of H7 decreased over the last three periods. This result provides an analytical confirmation of the call by the UN for more global efforts toward SDGs (UN, 2018).

To illustrate the above DEA transformation guidance for a given country, let us consider the United Kingdom (UK) with EGDI data for the period 2018 (see Table 8). On the one hand, the DEA-O model generates an effectiveness score of 0.98 for the UK. As it has an effectiveness score of less than one, the UK is considered ineffective when compared to DK and the KR. The DK and KR form the set of best-practice peers for the UK to benchmark for improvement and partnership. On the other hand, the DEA-I model generates an efficiency score of 0.91 for the UK. As it is inefficient, its set of best-practice peers consists of the DK, KR, and Monaco. Both DEA-O and DEA-I models generate improvement targets on how to reduce inputs to become efficient or how to increase outputs to become effective. The recommendations in terms of percentage changes are provided in Table 8. The decision-makers would then be able to develop a national strategy for improvement based on either input-efficiency or output-effectiveness recommendations according to the UK's vision and mission. For instance, the UK can become input-efficient, if it can develop a strategy to improve its TII and HCI utilization of resources with projected reduction targets of −8.12% while keeping its current service level constant, as shown in the bottom rows of Table 8.

Further, the DEA results are depicted graphically in Fig. 7 for the low-income versus high-income nations. The 31 low-income countries are represented by circle marks, while the 65 high-income countries are denoted by cross marks. The scatter plot of DEA-I and DEA-O scores for each country are plotted for 2014, 2016, and 2018. A country positioned above the DEA-O or DEA-I average lines is considered above-average input-efficient or above-average output-effective. From Fig. 7, one can observe the digital divide in performance between the low and high-income countries. Most low-income countries are clustered in the bottom left quadrant across the years. This cluster reflects that they are neither output-effective nor input-efficient. From an input-oriented perspective, those countries do not efficiently utilize their allocated resources to EG development (i.e., fewer resources can be used by all those countries to generate the same level of outputs). There might be high levels of investment in ICT, which are not appropriately translated into EG services. In this context, low-income nations can focus on ICT related success stories by benchmarking and collaborating with best performing peer countries to learn better resource utilization management, as well as setting improvement targets concerning these countries. From an output perspective, most low-income countries are below average (i.e., better online services can be achieved using the same level of input). The low output-effectiveness reflects that the low-income countries lack the know-how of maximizing EGDI performance. It can be due to several reasons, including management issues, a lack of process knowledge, or absence of collaboration among the different entities involved in the delivery of EG services. Such deficiencies can be made more granular by opening the EGDI indicators and running further DEA analysis to generate recommendation targets at lower indicator levels.

For the high-income countries, we also notice that more countries are

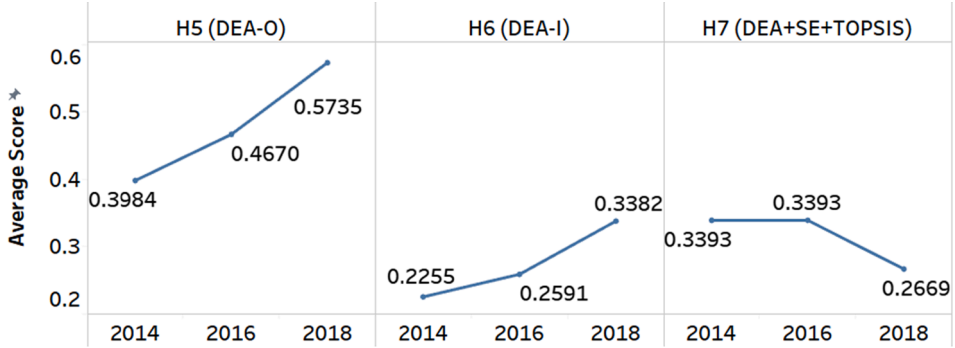

Fig. 6. Impact of Weights on Aggregation of Efficiency and Effectiveness Scores.

Table 8
DEA Improvement Targets for United Kingdom Effectiveness and Efficiency Measures.

DEA_Effectiveness_Score = 0.98	EGDI Z_Scores	DEA-O Projected targets	Difference	% change
TII	0.1996	0.1996	0	0.00%
HCI	0.08	0.056459	−0.023541	−29.43%
OSI	0.9792	0.998956	1.98E−02	2.02%
DEA_Efficiency_Score = 0.91	EGDI Z_Scores	DEA-I Projected targets	Difference	% change
TII	0.1996	0.183401	−1.62E−02	−8.12%
HCI	0.08	7.35E−02	−6.49E−03	−8.12%
OSI	0.9792	0.9792	0	0.00%

gradually becoming more input-efficient and output-effective (i.e., moving to the top right quadrant). The top right quadrant contains 50% of countries for 2014, 61% for 2016, and 68% for 2018. In 2018, while most countries are in the above-average efficient and effective quadrant, some countries (around 30%) are still not input-efficient, and some minorities (about 11%) are neither input-efficient nor output-effective. Similarly, such inefficient countries can use benchmarking analysis to set targets for improvement. An interesting observation from Fig. 7 is that across the years, both the overall averages of output-effectiveness and input-efficiency scores have been increasing, although the rate of increase is higher for the output-effectiveness value than the input-efficiency scores (from 0.48 to 0.65 vs. from 0.31 to 0.44). These results reflect an overall improvement in the EG delivery of online services at the expense of less efficient utilization of inputs. Therefore, it is not enough for a nation to move from one quadrant to another—it should move in the right direction to a more input-efficient and output-effective quadrant.

For another illustration of DEA insights and findings, we focus on the Middle East and North African (MENA) region with an efficiency and effectiveness performance visualization presented in Fig. 8. The AE is one of the best performers in the top quadrant. In 2014, AE was highly output-effective with a score of 0.9 and was much less input-efficient with a score of 0.2 (i.e., not efficient in using its resources to deliver EG services). In subsequent years (2016 and 2018), AE has annually improved its input-efficiency scores while maintaining its effectiveness of online services.

The potential justification behind this improvement is that in 2018, AE had put extra effort to raise the human capital awareness (i.e. improve HCI input score) and e-participation using various social media and communication platforms (Toshio, 2018). This indirectly contributed to the improvement of the resource consumption and the usage of the delivered EG services, and subsequently improved the AE efficiency input score. A potential recommendation to countries that are in similar positions to AE's for 2014 (i.e., good effectiveness but low efficiency), such as Bahrain, Oman, and Qatar is to follow a similar strategy to AE based on increasing public awareness and e-participation in online services. The proposed output-effectiveness and input-efficiency performance models, coupled with appropriate visual tools, are shown to potentially ignite further insights and guidance for managerial actions toward achieving SDGs.

5. Discussion

The results of this paper shed light on some of the key aspects to consider when developing data-driven performance evaluation methods to generate analytic insights and recommendations to derive managerial actions for better achievements of SDGs. The findings rely on theoretically based methods of performance evaluation. The empirical results show that the choice of a particular analytical method has a significant impact on the derivations of ranks and benchmarking recommendations for improvements. Existing approaches of SDG evaluation can provide average national trends (Lafortune et al., 2018; Schmidt-Traub et al., 2017) but cannot offer individual suggestions on how to improve the performance of a country. Furthermore, most methods still rely on biased assumptions of equal weights for sub-indices (Booysen, 2002; Lafortune et al., 2018). Our proposed method is based on a hybrid combination of performance evaluation models. We suggest using adaptive weighting methods to reflect the change in the development of indices, coupled with more granular country-specific insights.

Although the currently used UN evaluation method (SAW) has some advantages in its simplicity and ease of use, its most significant disadvantage emerges from the lack of analytical insights. Alternative data analytics methods can create data-driven weights and identify benchmarking either by comparison to ideal best and worst performers or establishing the best-practice frontiers, or efficient set of peer performers. Thus, the choice of a performance method should align with the desired goals and objectives. If we were to generate continuous improvement methods for SDGs, the chosen method should reflect reality and not inflate performance, be free from a compensation effect among indicators, provide more objective than subjective judgment, and rely on a proper weighting scheme to reflect performance change in indicators. However, if the objective is to determine the importance of indicators by weight, then applying the SE algorithm would be more appropriate and relevant to periodically measure the degree of change in the development needed on the given indicators. Moreover, if the objective is to provide proper managerial guidelines on how to improve SD, then using appropriate analytics methods, such as TOPSIS, can help identify relative benchmarks based on the deviation from the ideal best and worst virtual countries. However, TOPSIS does not indicate the efficiency of resource utilization by a country and the effectiveness of the transformation of such resources into effective outcomes. It also does not identify the real benchmark of aspirant peers to set targets for improvements. Hence, DEA is the recommended method to fill this current gap for generating innovative data-driven analytical insights. Additionally, the importance of DEA over SAW can be demonstrated using the results of H4 (SAW+SE+TOPSIS) in Fig. 5 with the results of H7 (DEA+SE+TOPSIS) in Fig. 6 using the SE weighting and TOPSIS approaches. H4 provides an increasing trend over the years, contrary to the efficiency and effectiveness results of H7, which support the UN's call for a greater global effort. This was not reflected in the UN's currently adopted method.

We demonstrated that it is possible to combine more than one analytical method to build on their combined benefits and strengths. For instance, TOPSIS, by default, performs a relative ranking of nations. Combining SE with TOPSIS ranking would generate a more adaptive weighting approach to conducting an enhanced relative ranking approach of countries. Additionally, although the DEA approach produced results close to SE with TOPSIS, DEA can also generate input-efficiency and output-effectiveness indices that cannot be obtained using the former. Further, DEA has its internal mechanisms to optimize the weights of indicators in the best interest of the country being evaluated. We generated input-efficiency and output-effectiveness scores for each country. However, if a single overall performance transformation efficiency based on both the efficiency and effectiveness indices is needed, then the SE method can be implemented to aggregate such measures as implemented in the proposed H7 (DEA+SE+TOPSIS) hybrid method.

More analytical insights and potential is hindered by the provision of EGDI data, as the OSI data is provided in an aggregate format. A call for developing a more comprehensive analytics roadmap is needed following the cognitive analytics management (CAM) framework for SDGs (Osman, Harfouche, Petter, & Jallouli, 2020). The CAM framework helps in identifying the SDG challenges and desired goals from all stakeholders' perspectives, for which, SMART indicators can be developed: "**S**pecific (with clear targets), **M**easurable (can be measured), **A**chievable (ambitious to motivate), **R**ealistic (feasible in order not to

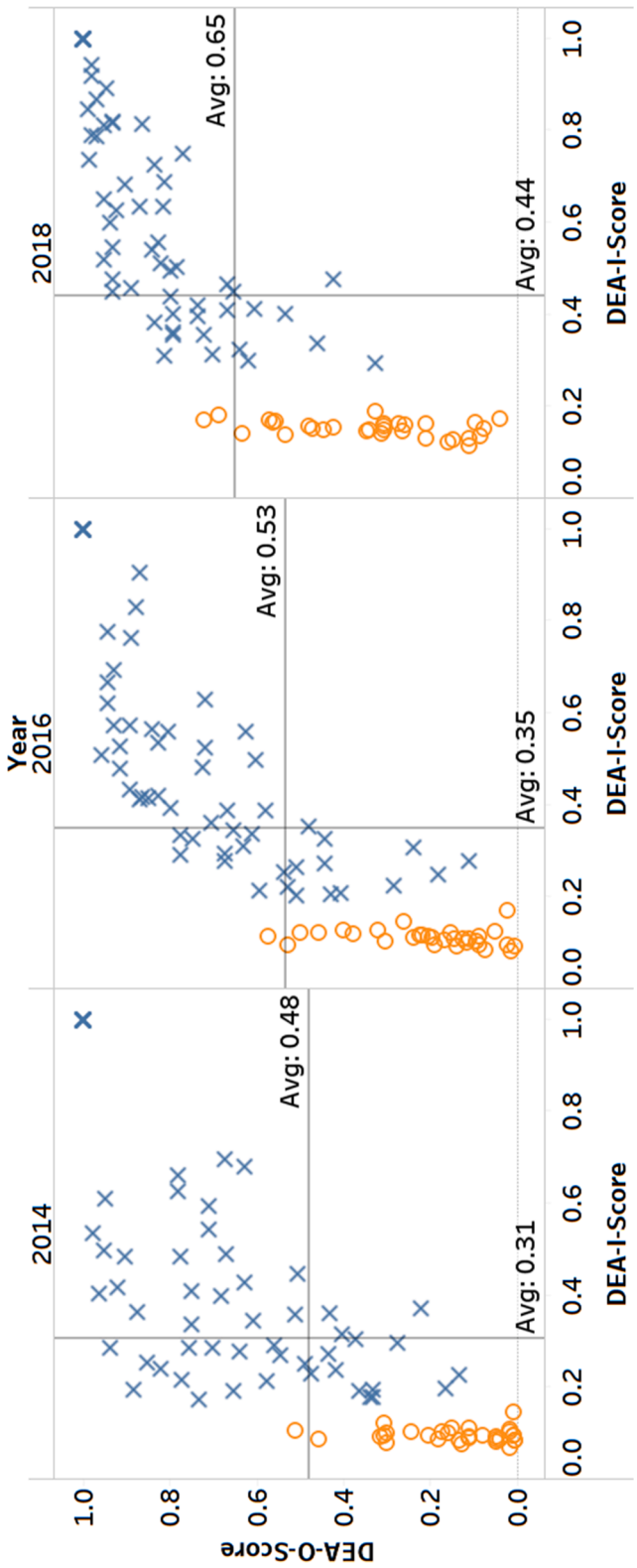

Fig. 7. Visualization of DEA Results of Low-Income (circle marks) versus High-Income (cross marks) Countries in 2014, 2016, and 2018.

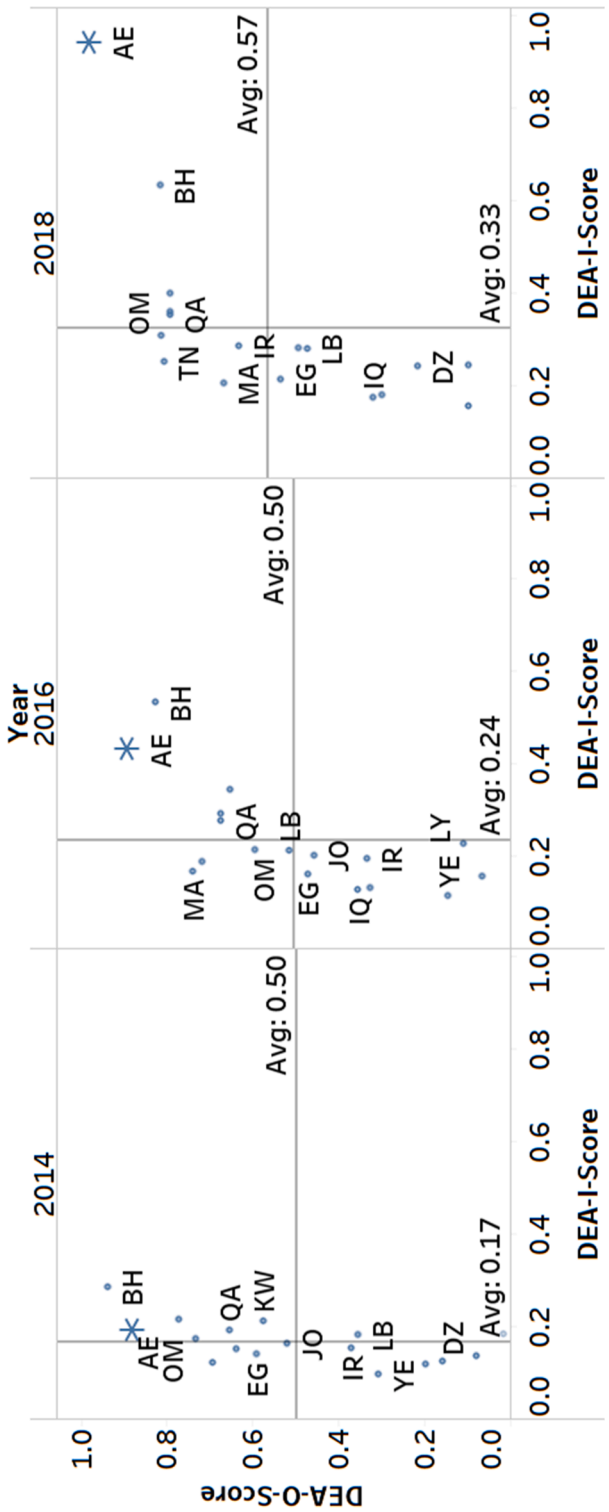

Fig. 8. Visualization of DEA Results for MENA Countries in 2014, 2016, and 2018.

discourage and demotivate) and Time-bound (have clear time deadlines to achieve and align effort)," through which an associated data strategy can be developed (Osman, Anouze, & Emrouznejad, 2014). The CAM framework would serve as a roadmap for better motivation, alignment, and choice of analytics performance evaluation tools along with the right management to design improvement strategy and establish

collaborative partnerships among aspirants and peers based on the proposed empirical benchmarking analytics results.

6. Conclusion

This article investigated the currently adopted UN methods for assessing the performance of nations toward achieving SDGs, through the re-evaluation of the EGDI. We identified some challenges associated with the current EGDI methodologies, for which we proposed new alternative modeling methods. The proposed methods included the use of various approaches to (1) process the data objectively and scientifically to derive weights for EGDI indicators; (2) provide a relative ranking of countries based on the relative distances from ideal best and worst countries rather than relying on an absolute ranking that leads to a ranking race without any benchmarking insights; and (3) introduce efficiency and effectiveness measures to guide the efficient utilization of resources to produce more efficient outputs and outcomes through the identification of improvement targets on a particular index by benchmarking with a set of best-practice and efficient peer countries. Our empirical results highlighted several findings on the EGDI progress over the last three evaluation periods, namely, 2014, 2016, and 2018.

First, it was found that the changes in values of the indices are important and their data-driven weights are different and not equal as set by the UN agencies. The weights of the EGDI were, on average, technology infrastructure (48%), online services (40%), and human capital (12%). Over the three periods, the data-driven weights showed an increasing trend for both the human capital and technology infrastructure and a decreasing trend for online services. The results highlighted that technology infrastructure is the main driving force behind the development of EGDI and SDGs, and more development is desired on the other indices. Consequently, the impact of using the newly data-driven weights on the aggregation of UN indices led to a significant change in the ranking of countries, and the ranking of 90% of countries changed.

Second, the newly introduced efficiency and effectiveness indices indicated that, on average, the world utilization of technology and human capital resources are efficient, and the developed online services and the impact on SDGs are effective, as both showed an increasing trend over the last three periods but with different growth rates. The world average of the effectiveness score of 0.47 is almost twice (1.75 times) the average of the efficiency score of 0.27. This indicates that the world is producing the current SDG outcomes at the expense of less efficient use of resources, reflecting the presence of unsustainable growth. The findings call for revisiting the current strategies and policies toward more sustainability by benchmarking and sharing best-practice development experiences through more collaboration and partnerships on SDGs.

Third, the proposed DEA models were shown to establish the best-practice benchmarks to identify peer countries for partnership and collaboration on SDGs, as well as setting the number of changes (improvement targets concerning aspirant peers) to reach the quadrant of both efficiency and effectiveness. The DEA models shed light on the weaknesses of the current UN absolute ranking method through the changes in the ranks of more than 95% of the countries.

Finally, based on the above findings on EGDI and SDGs through the provision of the newly proposed testing models and tools, we invite the various UN agencies to change their evaluation methods. It is possible to follow and implement the above-suggested approaches as most of the SDG data are analyzed similarly. Consequently, the proposed approaches can guide countries toward a more efficient transformation to reach their SDGs.

Some research limitations must be highlighted. First, the current techniques applied do not allow providing concrete recommendations at the sub-indicator level of SDGs due to the UN provision of aggregated data. As a result, we call on the UN agencies to provide more detailed and granular online survey data on SDGs. Second, the current study provided serval approaches to mitigate the weakness of the exciting UN ranking method and demonstrated the need to revise it. The proposed DEA and TOPSIS were found to be viable alternatives. However, the choice between TOPSIS and DEA depends on the complexity and desired analytics guidance to align, collaborate, and improve toward achieving SDGs. Although DEA is the preferred method because of its various advantages, it is more complex compared to TOPSIS, which requires a simple modification to the existing UN method. Thus, a trade-off must be made between the richness of insights generation and the complexity of the adopted method.

Further research could be conducted in several directions. First, it is worth investigating the potential to develop a single overall evaluation index of SDGs for each country. Second, the data collection and publication process performed by the UN agency should be revisited to minimize bias. An initial suggestion is to call for the provision of original raw data on indicators. Third, another future research direction is to develop efficiency and effectiveness measures for the TOPSIS method. Last, in our study, we have assumed the accuracy of certainty in quality data. If this assumption is questioned, fuzzy approaches may be used for data with uncertainty (Crespo & Crespo, 2016; Kacem et al., 2019; Suh et al., 2019).

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