International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-5, January 2020

New Weighting System for E-Readiness Indicators Based on Indicator Importance Measurement by the Random Forest Algorithm

Lamriq Rabii, Belkhayat Najib, Doukkali Abdelaziz

Abstract*: Weighting the indicators is always a difficult step in building composite indicators. In the e-readiness assessment approaches, where there are several indicators of different categories, the weighting methods used are not effective enough to assess the importance and the real priority of the indicators. The goal of this article is to improve the weighting methods used in e-readiness assessment tools by proposing two contributions. The first consists in combining subjective weighting with objective weighting to build a complete and optimal weighting system. The second contribution aims to propose a new statistical method based on the random forest algorithm to measure the importance of indicators and calculate objective weighting. A case study on the Internet Inclusive Index of 2019 is illustrated to assess the effect of the new weighting system on the scores and ranking of 100 countries.

***Keywords*: Combination weighting, objective weighting, subjective weighting, e-readiness, variable importance.**

I. INTRODUCTION

Composite indicators are a widely used tool in the calculation of sustainability indices that group several individual indicators. Its principle is: (1) select a set of individual indicators considered relevant for evaluating a definite goal; (2) standardize the indicators in order to align them in a single common scale; (3) weight the indicators by assigning an importance coefficient to each of them; and (4) aggregate the weighted indicators by a mathematical method to obtain the final index which comprises them [1],[2],[3].

Each step in the composite indicator construction has an influence on the final index value. In the case of building indices to rank countries, such as the Human Development Index or the Digital Access Index, the selection of indicators is not a too delicate phase. Indeed, in each area, there are many worldwide recognized organizations which can provide studies and guides for indicator selection based on experts in the fields and empirical studies [4]. Generally, the indicator selection step does not present a big challenge, but it evolves slowly by the introduction of new indicators due to the appearance of new technologies like the fifth generation in cellular networks (5G), artificial intelligence, etc.[5],[6].

Standardization is also an important step in the processing of composite indicators. It is a mathematical method which has the role of transforming the units of measurement of individual indicators and making them homogeneous and aligned in a single common scale. There are many mathematical normalization formulas, and the choice of a method does not impact the final index but rather the real value of the indicator and the comparison results [7].

After normalization, there comes the most complex step: the weighting of the indicators in order to aggregate them and find the final index value. Indeed, the weighting consists in assigning a coefficient to each individual indicator which reflects its importance in the evaluation. The variation in the weights has a great impact on the index scores and the ranking results [8]. In literature reviews, there are two types of weighting used in composite indicators [9], [10], [11]:

- Objective weighting: the coefficients assigned to the indicators come from one or a combination of several statistical methods which use the characteristics of the data from the set of individual indicators. These coefficients reflect only the inter-indicator importance and do not depend on the final goal of the index evaluation.
- Subjective weighting: the coefficients assigned to the indicators are based on the opinions of experts in the area of evaluation. This approach clearly shows that the proposed coefficients are directly related to the goal which the composite indicators want to evaluate and does not depend on the data characteristics of the set of indicators.

Each weighting approach has its advantages and disadvantages. Subjective weighting benefits from experience based on expert judgment and does not consider the statistical properties of the indicators. In addition, in the case of a very large number of indicators, the judgment cannot be reliable and effective because of low experience for certain indicators and the absence of information on the correlation or the relationship between indicators.

Manuscript published on January 30, 2020.
* Correspondence Author
Lamriq Rabii*, TIES team, ENSIAS, MedV Souissi University, Rabat, Morocco. Email: 1amriq.rabii@gmail.com
Belkhayat Najib, LAMAI, Cadi Ayyad University, Marrakech, Morocco. Email: najib.belkhayat@gmail.com
Doukkali Abdelaziz, TIES team, ENSIAS, MedV Souissi University, Rabat, Morocco. Email: doukkali@gmail.com

On the other hand, objective weighting is only based on the statistical characteristics of the indicators and the link between them. Also, the lack of experience and information on the purpose of evaluation make this approach neutral and insufficient to assess the importance of indicators for the purpose of evaluation [12], [13].

Thus, the choice between these two approaches is not linked to a preference or condition. Indeed, from a set of individual indicators, we can measure several indices including different goals by applying, for each goal to be evaluated, a subjective weighting which corresponds to it. However, objective weighting does not allow multiple goals to be assessed by changing the statistical method. This is because objective weighting only depends on the characteristics of the data of the selected indicators. This shows that each approach addresses a necessary aspect but is not sufficient. Consequently, the two approaches are necessary since one completes the other to build a global and relevant weighting. Several researchers have proposed the combination of subjective weighting and objective weighting to build a single comprehensive and efficient weighting system. However, in the evaluation of e-readiness, no method of combining objective and subjective weighting was used to calculate the composite index [3], [14].Table I shows the weighting methods used by the best-known e-readiness indices.

Table I: Weighting methods for e-readiness indexes

E-readiness Index	Weighting method	Weighting approach
ICT Development Index	PCA	Objective
Networked Readiness Index	Equal weighting	Subjective
United Nations Conference on Trade and Development (UNCTAD)	Equal weighting	Subjective
Technology Achievement Index	Equal weighting	Subjective
Inclusive Internet Index	Expert opinion	Subjective
Digital Economy and Society Index	Proposed by designer	Subjective
Information Society Index		
Digital Access Index	Equal weighting within category	Subjective
Digital Opportunity Index	Equal weighting within category	Subjective

We note that the majority of e-readiness composite indices use subjective weighting against a minority who use statistical methods. To remedy this problem, we proposed two contributions to improve the objective weighting and combined it with the subjective weighting given by the designer:

(1) Proposal for a new statistical method based on the inter-indicator importance measure for the calculation of objective weighting.

(2) Application of a method of combining subjective weighting and objective weighting to build a complete weighting system.

The rest of this article is organized as follows: The methodology is presented in Section 2. The steps for determining the weights are in Section 3. Next, we illustrate a case study in Section 4. Then, comparisons and discussion are detailed in Section 5. Finally, conclusions are drawn in Section 6.

II. METHODOLOGY

In this study, we have proposed a new statistical method for calculating objective weighting. This method is based on measuring the importance of variables using the random forest algorithm. We then combined this new weighting with the subjective weighting which is often proposed by the designers of the index according to the goal to be evaluated.

A. Variable importance

The concept of importance of variables is defined as a statistical approach which aims to evaluate the relationship of each variable with the dependent output variable. In regression and classification models, the measure of the importance of variables can be used for two reasons [15]:

- To find a selection of the relevant variables which constitute a reduced number of sufficient predictors to produce a good prediction of the output variable. This approach, called “variable selection”, is used to reduce the size of the data when the number of variables is large.
- To assess the importance of each variable in relation to the response variable for the purpose of explaining or interpreting the model. This approach is used in linear regression models to identify the effect or impact of each variable on the output response.

For years, several methods of measuring variable importance have been studied in the literature: LMG and PMVD in linear regression, Random Forest [15], variable importance measures (VIM) based on difference, parametric regression and associated VIMs, nonparametric regression techniques, forest-based random VIMs, hypothesis testing techniques, variance-based VIMs, moment-independent VIMs and graphical VIMs [16]. Other techniques for measuring the importance of variables for reasons of interpretation of the models are examined in the article [17].

In this article, we used the random forest algorithm as a method of measuring importance with the use of the backward selection procedure RFE to correct the effects of the correlation. Each method has its advantages and disadvantages. In the article [16], the author has shown that the choice of an important measurement method depends on the characteristics and dimensions of the data. In the case of evaluation of the e-readiness composite indices, the number of indicators exceeds 50 per 100 to 150 countries. Consequently, the random forest algorithm is the most efficient since it is recommended for “large P, small N” problems, where P is the number of variables and P is the number of observations. In this article, we have chosen the random forest algorithm as the importance measurement method with the use of the backward selection procedure RFE to correct the effects of the correlation.

B. Random forest

The random forest algorithm is a nonparametric method widely used in classification and regression models. It shows its effectiveness in predicting large problems. Also, it is used as an approach for selecting the relevant variables through the measurement of their importance.

Introduced by Breiman in 2001, its principle consists in combining the result of a large number of random trees formed from bootstrap samples of the training data. In fact, in each constructed tree, the sample of observations and the variables are selected randomly. So, the objective of the random forest algorithm is to average the forecasts of random trees constructed to reduce the variance and therefore the forecast error [18], [19].

C. The importance measure by permutation

The random forest algorithm also assesses the importance of criterion variables for predicting the output variable or to interpret the effect/impact of each variable. To measure the importance of a variable X_j to predict the output variable Y, Breiman proposed to disrupt the link between X_j and Y by a random permutation of the values of X_j. More formally, we denote by S_n the set of learning samples of n random vectors $(X^{(j)}, Y_j)$ with j=[1,…,n] and $X^{(j)} = (X_1^{(j)}, X_2^{(j)}, \dots, X_p^{(j)})$. If $f(x) = E[Y|X = x]$ is the function to be estimated by regression, then the error committed is:

$$\hat{E}_f = \mathrm{E}\left[\left(\hat{\mathrm{f}}(\mathrm{X}) - \mathrm{Y}\right)^2\right] \quad (1)$$

By considering an empirical estimator based on the validation sample $\bar{S}$, we then obtain:

$$\hat{E}_{\hat{f},\bar{S}} = \frac{1}{\bar{S}} \sum_{i:(X^{(i)},Y_i)\in\bar{S}} \left(Y_i - \hat{f}(X^{(i)})\right)^2 \quad (2)$$

From p_{tree} bootstrap samples $S_n^1, S_n^2, \dots, S_n^{ptree}$, training data S_n and a collection of estimators $\hat{f}_1, \hat{f}_2, \dots, \hat{f}_{ptree}$, we constitute a collection of out-of-bag (OOB) sets, $\{\bar{S}_n^k = Sn \setminus Snk,\ k=1\dots ptree,$ containing only the observations not retained in the bootstrap samples. By permuting the values of the i-th variable of the OOB samples, we obtain the permuted OOB sets $\{\bar{S}_n^{ki}, k = 1 \dots p_{tree}, i = 1 \dots n\}$. The measure of importance by permutation is calculated by formula (3), [17]:

$$\hat{I}(X_i) = \frac{1}{p_{tree}} \sum_{k=1}^{p_{tree}} \left[\hat{E}_{\hat{f}_k,\bar{S}_n^{ki}} - \hat{E}_{\hat{f}_k,\bar{S}_n^k}\right] \quad (3)$$

D. Correlation and importance measurement

The effect of correlation on the measure of importance has been studied and examined in several research articles. In fact, some methods of variable importance measures are not effective if the variables are correlated. Moreover, this is the case for several studies. In article [20], the author has shown that correlation has an effect on the measure of importance. To correct this effect, the author applied the Recursive Feature Elimination (RFE) algorithm to the random forest method as follows:

- 1: Execute the random forest algorithm.
- 2: Measure the importance of the variables.
- 3: Save the least important variable and remove it from the list of variables.
- 4: Repeat steps 1 to 3 on the list of remaining variables until all the variables are eliminated.

III. DETERMINATION OF THE TOTAL WEIGHT

From a set L of N individual indicators $X_i = (x_{i1}, x_{i2}, \dots, x_{iM}); i = 1 \dots N.; j = 1 \dots M$,select and normalize the indicators to evaluate M countries $P_j; j = 1 \dots M$ according to a given goal B characterized by the index I_j as follows:

$$I_j = \sum_{i=1}^{N} v_{ij}\, w_i^T \quad (4)$$

v_{ij} is the normalized value of the indicator X_i for the country P_j, and w_i^T is its coefficient of the total weighting with $W^T = (w_1^T, w_2^T, .. w_N^T)$, the combination of the objective weighting W^O and the subjective weighting W^S.

To determine the total weighting W^T, we followed the steps below:

Step 1: Determining the objective weighting

Objective weighting is calculated using the indicator importance measurement method based on the random forest algorithm described in Section 2. Indeed, in a set L of indicators, we note Im_{ij}, the measure of importance of the indicator X_i for the indicator X_j, and M_{imp}, the matrix of importance between individual indicators shown in (5). We consider $Im_{ii} = 0$.

$$M_{imp} = \begin{bmatrix} Im_{11} & \cdots & Im_{N1} \\ \vdots & Im_{ij} & \vdots \\ Im_{1N} & \cdots & Im_{NN} \end{bmatrix} \quad (5)$$

Let Im_i be the total importance of an indicator X_i in the set L of indicators, i.e. the sum of the measures of importance of the indicator X_i for each indicator $X_{j\,(j\neq i)}$, Then,

$$Im_i = \sum_{\substack{j=1 \\ j\neq i}}^{n} Im_{ij} \quad (6)$$

is the measure of global importance Im_i of the indicator X_i in the set L of indicators and represents the measure of usefulness and influence of X_i on the rest of the individual indicators X_j $(j \neq i,\ j \in [1 \dots N]$ .By normalizing the importance values of each indicator, we obtain the coefficients of the objective weighting W^O by (7):

$$W^O = Im_i / \sum_{i=1}^{n} Im_i \quad (7)$$

Step 2: Determining the subjective weighting

In this article, we have not proposed methods to calculate the subjective weighting, but we have used the weighting proposed by the index constructor. This weighting is generally determined by a synthesis of the opinions of several experts specialized in the area of evaluation who judge by experience the importance and the priority of each indicator according to the aim of evaluation.

Step 3: Determining the total weighting

The approach used to combine objective weighting and subjective weighting is based on the principle of variance maximization as follows [11]:

Let

Retrieval Number: E7032018520/2020©BEIESP
DOI:10.35940/ijrte.E7032.018520
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

$W^O = (w_1^o, w_2^o, \dots, w_N^o)$ be the vector of objective weighting with $w_i^o > 0$ and $\sum_{i=1}^{N} w_i^o = 1$ obtained in step 1, and let $W^S = (w_1^s, w_2^s, \dots, w_N^s)$ be the vector of subjective weighting with $w_i^s > 0$ and $\sum_{i=1}^{N} w_i^s = 1$ obtained in step 2. To benefit from the advantages of each weighting and reduce their limitations, we combine the two weights W^O and W^S to build a single complete and global weighting vector by the following formula:

$$W^T = \alpha W^O + \beta W^S \tag{8}$$

(α, β) are the linear combination coefficients. $\alpha \geq 0, \beta \geq 0$, and the two coefficients satisfy the following condition:

$$\alpha + \beta = 1 \tag{9}$$

In the case of evaluation of an index for several countries, if the indicator values X_i are the same for all the M countries or if there is no obvious difference between them, this indicator has no influence on the evaluation results of these countries, so it will have null or very little weight. On the other hand, if there is a large difference between the values of an indicator for the M countries, the indicator will have a great effect on the evaluation results of the countries, and therefore its weight will be very high. In other words, the degree of difference in the values of an indicator j in all countries reflects the level of influence of the indicator on the evaluation results of these countries. The principle of this method is inspired by information theory which shows that the greater the quantity of information given by an indicator, the greater its weight [21]. In statistics, the variance reflects the degree of difference, and according to the principle of variance maximization, the optimal weighting vector should maximize the total variance of all the indicators for all the evaluation countries [11],[22]. This is mathematically translated by the following linear equation:

$$\begin{aligned} Max\ V &= \sum_{i=1}^{N} V_i(w) \\ &= Max \sum_{j=1}^{N} \frac{1}{M} \sum_{i=1}^{M} \left(x_{ij} - \bar{x}_{ij}\right)^2 {w_j^T}^2 \\ &= Max \sum_{j=1}^{N} \sum_{i=1}^{M} \left(x_{ij} - \bar{x}_{ij}\right)^2 \left(\alpha w_j^o + \beta w_j^s\right)^2 \end{aligned} \tag{10}$$

where $\alpha + \beta = 1, \alpha \geq 0, \beta \geq 0$

$v_j = \frac{1}{M} \sum_{i=1}^{M} (x_{ij} - \bar{x}_{ij})^2$ is the variance of the indicator X_j. x_{ij} is the value of the indicator X_j for the country P_i. $\bar{x}_{ij} = \frac{1}{M} \sum_{j=1}^{M} x_{ij}$ is the arithmetic mean of the normalized values of the indicator j.

To solve the optimization problem in (10), consider the following Lagrange function:

$$L(\alpha, \beta, \delta) = \sum_{j=1}^{N} v_j \left(\alpha w_j^o + \beta w_j^s\right)^2 + \delta(\alpha + \beta - 1) \tag{11}$$

where δ is the Lagrange multiplier. Let $\partial L/_{\partial\alpha} = 0$, $\partial L/_{\partial\beta} = 0$, and $\partial L/_{\partial\delta} = 0$. Therefore,

$$\sum_{i=j}^{N} v_j w_j^o \left(\alpha w_j^o + \beta w_j^s\right) + \delta = 0 \tag{12}$$

$$\sum_{i=j}^{N} v_j w_j^s \left(\alpha w_j^o + \beta w_j^s\right) + \delta = 0 \tag{13}$$

And $\partial L/_{\partial\delta} = 0$ gives $\alpha + \beta = 1$. From (12) and (13), we get:

$$\sum_{i=j}^{N} v_j w_j^o \left(\alpha w_j^o + (1-\alpha) w_j^s\right) = \sum_{i=j}^{N} v_j w_j^s \left(\alpha w_j^o + (1-\alpha) w_j^s\right) \tag{14}$$

Hence, we determine the two coefficients α and β as:

$$\alpha = \frac{\sum_{i=j}^{N} v_j w_j^s \left(w_j^s - w_j^o\right)}{\sum_{i=j}^{N} v_j \left(w_j^s - w_j^o\right)^2} \tag{15}$$

$$\beta = \frac{\sum_{i=j}^{N} v_j w_j^o \left(w_j^o - w_j^s\right)}{\sum_{i=j}^{N} v_j \left(w_j^s - w_j^o\right)^2} \tag{16}$$

After obtaining the two coefficients α and β, we can calculate the total weighting $W^T = \alpha W^O + \beta W^S$ .The evaluation index of each country is calculated by the following equation:

$$I_i = \sum_{j=1}^{N} x_{ij} w_j^T \tag{16}$$

The variance maximization approach allows by an optimal way to combine objective weighting and subjective weighting and take advantage of their benefits and better assess the index of each country.

IV. CASE STUDY: INCLUSIVE INTERNET INDEX

The Inclusive Internet Index (III), mandated by Facebook and managed by The Economist Intelligence Unit (EIU), was created in 2017 as a rigorous benchmark in terms of internet inclusion at the national level in four categories: Availability, Affordability, Relevance and Preparation. The index covers around 100 countries for the year 2019 and measures perceptions of how internet use affects people's lives and their livelihoods [23].

A. Data of index III

The index is composed of 53 indicators divided into four categories and 11 subcategories as illustrated in Table II.

Table II: List of categories and subcategories of III indicators

Categories	Subcategories	Code	Indicator
1- AVAILABILITY	1- USAGE	1.1.1	Internet users
		1.1.2	Fixed-line broadband subscribers
		1.1.3	Mobile subscribers
		1.1.4	Gender gap in internet access
		1.1.5	Gender gap in mobile phone access
	2- QUALITY	1.2.1	Average fixed broadband upload speed

		1.2.2	Average fixed broadband download speed
		1.2.3	Average fixed broadband latency
		1.2.4	Average mobile upload speed
		1.2.5	Average mobile download speed
		1.2.6	Average mobile latency
		1.2.7	Bandwidth capacity
	3- INFRASTRUCTURE	1.3.1	Network coverage (min. 2G)
		1.3.2	Network coverage (min. 3G)
		1.3.3	Network coverage (min. 4G)
		1.3.4	Government initiatives to make Wi-Fi available
		1.3.5	Private sector initiatives to make Wi-Fi available
		1.3.6	Internet exchange points
	4- ELECTRICITY	1.4.1	Urban electricity access
		1.4.2	Rural electricity access
2- AFFORDABILITY	1- PRICE	2.1.1	Smartphone cost (handset)
		2.1.2	Mobile phone cost (prepaid tariff)
		2.1.3	Mobile phone cost (postpaid tariff)
		2.1.4	Fixed-line monthly broadband cost
	2- COMPETITIVE ENVIRONMENT	2.2.1	Average revenue per user (ARPU, annualized)
		2.2.2	Wireless operators' market share
		2.2.3	Broadband operators 'market share
3- RELEVANCE	1- LOCAL CONTENT	3.1.1	Availability of basic information in the local language
		3.1.2	Concentration of websites using country-level domains
		3.1.3	Availability of e-Government services in the local language
	2- RELEVANT CONTENT	3.2.1	e-Finance content
		3.2.2	Value of e-finance
		3.2.3	e-Health content
		3.2.4	Value of e-health
		3.2.5	e-Entertainment usage
		3.2.6	e-Commerce content
		3.2.7	Value of e-commerce
4- READINESS	1- LITERACY	4.1.1	Level of literacy
		4.1.2	Educational attainment
		4.1.3	Support for digital literacy
		4.1.4	Level of web accessibility
	2- TRUST & SAFETY	4.2.1	Privacy regulations
		4.2.2	Trust in online privacy
		4.2.3	Trust in Government websites and apps
		4.2.4	Trust in non-government websites and apps
		4.2.5	Trust in information from social media
		4.2.6	e-Commerce safety
	3- POLICY	4.3.1	National female e-inclusion policies
		4.3.2	Government e-inclusion strategy
		4.3.3	National broadband strategy
		4.3.4	Funding for broadband build out
		4.3.5	Spectrum policy approach
		4.3.6	National digital identification system

The methodology used by the index III to calculate the country scores is based on the following steps:

- ***Data normalization:*** the index uses the max-min transformation method with the following formula:

$$X_{norm} = (x - Min(x))/(Max(x) - Min(x)) \quad (17)$$

  where Min(x) and Max(x) are, respectively, the lowest and highest values in the 100 countries for a given indicator x. The value then goes from a scale of [0–1] to [0–100] to make it directly comparable to other indicators.
- ***Estimating missing data***: The EIU uses statistical methods to estimate missing values that could not be obtained from comparable series or historical data. The regression approach based on the ordinary least squares method was used to predict the missing data.
- ***Weighting and aggregation***: The final score is calculated by aggregating the weighted indicators according to their importance. The EIU considers the weights as an implicit compromise between the sub-dimensions of an indicator. As such, the EIU consulted individual experts to assess the importance of each indicator of internet inclusion.

B. Calculating the weight of the index III

To calculate the new combined weighting W^T, we followed the steps mentioned in Section 3. The data of index III used to calculate the objective weighting W^O are obtained from the official website of the index III [24]. The III dataset contains 53 indicators for 100 countries. The indicator values are all complete and normalized on a scale of [0–100] according to the max-min transformation method shown in (17).

Step 1: Objective Weighting

The importance of each indicator is calculated using the steps cited in Section 2-D. By normalizing the importance vector, we obtain the objective weighting W^O. Table III shows the objective weights for the 53 indicators of the index III.

Table III: The objective weighting for the 53 indicators of the index III

Indicator	W^O	Rank	Indicator	W^O	Rank
1.1.2	0.0872	1	4.2.5	0.0097	28
1.2.5	0.0630	2	1.3.6	0.0090	29
4.1.1	0.0626	3	3.2.4	0.0080	30
3.2.6	0.0624	4	3.2.5	0.0078	31
4.1.2	0.0479	5	3.2.7	0.0078	32
1.1.1	0.0478	6	1.1.3	0.0075	33
1.2.7	0.0435	7	1.3.1	0.0069	34
1.3.3	0.0424	8	3.2.2	0.0062	35
2.1.4	0.0422	9	3.2.3	0.0027	36
1.2.2	0.0400	10	4.3.1	0.0019	37
1.4.2	0.0335	11	4.1.4	0.0018	38
1.2.6	0.0312	12	3.1.3	0.0018	39

1.2.3	0.0300	13	4.3.5	0.0016	40
1.2.1	0.0300	14	1.3.5	0.0016	41
1.4.1	0.0276	15	3.1.2	0.0013	42
1.3.2	0.0275	16	2.2.2	0.0011	43
2.1.1	0.0262	17	4.3.2	0.0011	44
1.1.4	0.0253	18	2.2.3	0.0011	45
1.2.4	0.0231	19	4.1.3	0.0010	46
2.1.2	0.0226	20	4.3.3	0.0008	47
2.1.3	0.0202	21	4.2.1	0.0008	48
4.2.4	0.0158	22	3.2.1	0.0007	49
2.2.1	0.0146	23	4.3.4	0.0005	50
1.1.5	0.0139	24	4.3.6	0.0004	51
4.2.2	0.0136	25	1.3.4	0.0004	52
4.2.6	0.0118	26	3.1.1	0.0002	53
4.2.3	0.0104	27			

Step 2: **Subjective Weighting**

The EIU consults the opinion of a group of experts in the evaluation area to assess the priority and importance of each indicator in internet inclusion. This weighting is considered subjective because it is based on expert judgment and only depends on the purpose of the evaluation. Table IV shows the subjective weights used by the index III.

Table IV: The subjective weighting for the 53 indicators of the index IV

Indicator	W^S	Rank	Indicator	W^S	Rank
2.1.4	0.0503	1	1.2.6	0.0143	25
1.4.2	0.0500	1	1.2.3	0.0143	25
1.4.1	0.0500	1	1.2.1	0.0143	25
2.1.1	0.0503	1	1.2.4	0.0143	25
2.1.2	0.0503	1	1.3.3	0.0100	32
2.1.3	0.0503	1	3.2.4	0.0100	32
3.1.3	0.0400	7	3.2.5	0.0100	32
3.1.1	0.0400	7	3.2.7	0.0100	32
2.2.2	0.0396	9	1.3.1	0.0100	32
2.2.3	0.0396	9	3.2.2	0.0100	32
1.1.2	0.0200	11	4.2.1	0.0094	38
3.2.6	0.0200	11	4.1.1	0.0083	39
1.1.1	0.0200	11	4.1.2	0.0083	39
1.3.2	0.0200	11	4.1.4	0.0083	39
1.1.4	0.0200	11	4.1.3	0.0083	39
1.1.5	0.0200	11	4.3.1	0.0060	43
1.3.6	0.0200	11	4.3.5	0.0060	43
1.1.3	0.0200	11	4.3.2	0.0060	43
3.2.3	0.0200	11	4.3.3	0.0060	43
1.3.5	0.0200	11	4.3.4	0.0060	43
3.1.2	0.0200	11	4.2.4	0.0047	48
3.2.1	0.0200	11	4.2.2	0.0047	48
1.3.4	0.0200	11	4.2.6	0.0047	48
2.2.1	0.0198	24	4.2.3	0.0047	48
1.2.5	0.0143	25	4.2.5	0.0047	48
1.2.7	0.0143	25	4.3.6	0.0030	53
1.2.2	0.0143	25			

Step 3: **Total Weighting**

After determining the objective weighting W^O and the subjective weighting W^S, we use the method of combining the weights based on the principle of maximizing the variance detailed in step 3 of Section III. We obtain the total combined weighting by $W^T = \alpha W^O + \beta W^S$. The coefficients α and β are determined using (14) and (15). We find: $\alpha = 0.3419$ and $\beta = 0.6580$. This result shows that the subjective weighting has an influence on the total weighting compared to the objective weighting. Next, the total weight W^T is calculated. The total weights are shown in Table V.

Table V: The total weighting for the 53 indicators of the index III

Indicator	W^T	Rank	Indicator	W^T	Rank
2.1.4	0.0475	1	1.3.6	0.0163	28
1.4.2	0.0444	2	1.1.3	0.0157	29
1.1.2	0.0430	3	3.2.3	0.0141	30
1.4.1	0.0423	4	1.3.5	0.0137	31
2.1.1	0.0420	5	3.1.2	0.0136	32
2.1.2	0.0408	6	3.2.1	0.0134	33
2.1.3	0.0400	7	1.3.4	0.0133	34
3.2.6	0.0345	8	3.2.4	0.0093	35
1.2.5	0.0309	9	3.2.5	0.0093	36
1.1.1	0.0295	10	3.2.7	0.0093	37
3.1.3	0.0269	11	1.3.1	0.0089	38
4.1.1	0.0268	12	3.2.2	0.0087	39
2.2.2	0.0264	13	4.2.4	0.0085	40
2.2.3	0.0264	14	4.2.2	0.0078	41
3.1.1	0.0264	15	4.2.6	0.0072	42
1.2.7	0.0243	16	4.2.3	0.0067	43
1.2.2	0.0231	17	4.2.1	0.0065	44
1.3.2	0.0226	18	4.2.5	0.0064	45
4.1.2	0.0218	19	4.1.4	0.0060	46
1.1.4	0.0218	20	4.1.3	0.0058	47
1.3.3	0.0211	21	4.3.1	0.0046	48
1.2.6	0.0201	22	4.3.5	0.0045	49
1.2.3	0.0197	23	4.3.2	0.0043	50
1.2.1	0.0196	24	4.3.3	0.0042	51
2.2.1	0.0180	25	4.3.4	0.0041	52
1.1.5	0.0179	26	4.3.6	0.0021	53
1.2.4	0.0173	27			

V. COMPARISON AND DISCUSSION

The results of the calculation of the objective weighting W^O show that the importance of the indicators based on the statistical characteristics of the data is different from the importance given by the subjective weighting based on the judgment of the evaluation experts of the index III. The correlation between W^O and W^S is 0.121. However, the correlation between W^C and W^S is 0.536. The combination coefficients calculated by the variance maximization method show that the W^S weighting is the most dominant. To better illustrate the effect of the combination of W^O and W^S weights, we compare the rank of indicators in the W^S weighting with W^C. Table VI presents the 10 indicators with the most remarkable difference in rank between the W^S and W^C weightings. It can be seen that the W^O weighting adjusts the W^S weighting by improving or degrading the weight of the indicators in the W^C according to the importance of the indicator in the W^O. For example, the ranking of indicator 4.1.1 (Literacy level) went from position 39 in the W^S weighting to position 12 in the W^C. Also, the ranking of indicator 4.1.2 (Level of education) improved from position 39 in W^S to position 19 in W^C. This is because, these two indicators are considered very important in the weighting objective. Besides, that explains why the developing countries which have a very high literacy rate and a very poor level of education, are always poorly classified in the evaluation of e-readiness indexes. This new weighting system therefore shows that education is a discriminating factor in the evaluation of the countries' e-readiness.

On the other hand, the ranking of indicator 1.3.4 (Government initiatives to make Wi-Fi available) is downgraded from position 11 in W^S to position 34 in W^C due to its low weighting in the W^O weighting. Indeed, there are only 16 countries among 100 which obtained a score 0. On the other hand, 84 countries have a score of 100. In addition, several countries with a score of 100 but classified under 80 like Madagascar, Benin and Angola . So the new ranking of indicator (1.3.4) in the combined weighting seems reasonable and cannot be equivalent to indicator 1.1.1 (internet use) or indicator 3.2.6 (E-commerce content) as proposed in the subjective weighting.

Table VI: Comparison between the top 10 important indicators in W^S, W^O and W^C

Indicator	$Rank^{SW}$	$Rank^{OW}$	$Rank^{CW}$	$Rank^{CW} - Rank^{SW}$
4.1.1 Level of literacy	39	3	12	−27
4.1.2 Educational attainment	39	5	19	−20
1.2.5 Average mobile download speed	25	2	9	−16
1.3.6 Internet exchange points	11	29	28	17
1.1.3 Mobile subscribers	11	33	29	18
3.2.3 e-Health content	11	36	30	19
1.3.5 Private sector initiatives to make Wi-Fi available	11	41	31	20
3.1.2 Concentration of websites using country-level domains	11	42	32	21
3.2.1 e-Finance content	11	49	33	22
1.3.4 Government initiatives to make Wi-Fi available	11	52	34	23

At the level of the 11 subcategories, Table VII indicates for the three W^O, W^S and W^C weights, the weight and the rank of each subcategory. In the W^S, several subcategories have the same importance. On the other hand, in the W^O, the subcategories have different weights. To measure the effect of the W^O weighting on the final weighting W^C, we compare the ranks of the subcategories in the W^S and W^C weightings. We note that there is a slight change in the values of the weighting, but the ranking of importance for the first-ranked subcategory and the last-ranked subcategory remains the same in the two weightings. Indeed, in the W^C, the subcategory Price is reduced by 3% compared to W^S. Thus, the subcategories Quality and Use experienced increases of 5.5% and 2.8%, respectively.

Table VII: Comparison of W^S, W^O and W^C for 11 subcategories

Subcategory	W^S (%)	Rank W^S	W^O (%)	Rank W^O	W^T (%)	Rank W^T
PRICE	20	1	11.13	4	17.03	1
QUALITY	10	2	26.07	1	15.50	2
USE	10	2	18.16	2	12.79	3
RELEVANT CONTENT	10	2	9.58	5	9.86	4
INFRASTRUCTURE	10	2	8.78	6	9.58	5
ELECTRICITY	10	2	6.11	8	8.67	6
COMPETITIVE ENVIRONMENT	10	2	1.68	9	7.09	7
LOCAL CONTENT	10	2	0.33	11	6.69	8
LITERACY	3.3	9	11.32	3	6.04	9
TRUST AND SECURITY	3.3	9	6.21	7	4.30	10
POLITICS	3.3	9	0.63	10	2.39	11

Finally, at the scale of the four categories, Table VIII shows that the importance rank of the four categories in the W^S remains the same in the combined weighting W^C. However, the W^S weighting values are changed slightly in the W^C. Indeed, the weight of the Availability and Preparation categories is increased by 6.5% and 2.73%, respectively. The weight of the Relevance and Affordability categories is reduced by 5.88% and 3.45%, respectively.

Table VIII: Comparison of W^S, W^O and W^T for four categories

Category	W^S (%)	Rank W^S	W^O (%)	Rank W^O	W^C (%)	Rank W^C
1.Availability	40	1	59.13	1	46.54	1
2.Affordability	30	2	12.81	3	24.12	2
3.Relevance	20	3	9.90	4	16.55	3
4.Preparation	10	4	18.16	2	12.73	4

To better illustrate the contribution of the new method of calculating the W^O weighting in the total W^C weighting, we compare, for the 100 countries, the index score III calculated by the W^S with the new score calculated by the W^C. Table IX presents the top 20 countries classified according to the new score III^{CW} based on the combined weighting W^C in comparison to the score III^{SW} based on the W^S used by the EIU. The total result of the 100 countries for the two scores is given in Table XI in the Appendix. The absolute average of the difference in ranks $\boldsymbol{Rank^{sw} - Rank^{cw}}$ is 2.94. The correlation between the two scores is 0.994. Singapore obtained the first score in the W^C, and Sweden obtained the second score. The ranking of countries has changed a lot due to the change in importance of certain indicators in the objective weighting such as: Fixed broadband subscribers, average mobile download speed, literacy level and education attainment.

Table IX: Top 20 best ranked countries according to the score III^{cw} in comparison to III^{sw}

Country	III^{PS}	$Rank^{PS}$	III^{PC}	$Rank^{PC}$	Difference $Rank^{PS} - Rank^{PC}$
Singapore	87.3	2	86.72	1	1
Sweden	89.5	1	86.23	2	−1
Denmark	85.9	4	83.6	3	1
Switzerland	84.1	14	83.35	4	10
South Korea	85.1	9	83.14	5	4
Spain	85.2	8	82.97	6	2
Canada	85.3	6	82.45	7	−1
UK	85.4	5	82.44	8	−3
United States	86.3	3	81.9	9	−6
Portugal	84.2	13	81.48	10	3
Finland	85.3	6	81.45	11	−5
France	84.9	10	81.38	12	−2
Japan	84.3	12	81.08	13	−1
Australia	83.6	15	79.92	14	1
Netherlands	80.5	29	79.82	15	14
Taiwan	81.6	22	79.71	16	6
Germany	82.7	18	79.64	17	1
Ireland	81.7	21	79.04	18	3
Belgium	81.4	25	78.96	19	6
Estonia	81.5	24	78.88	20	4

To measure the effectiveness of the method of combining the W^O and W^C weights, we compare the ranking of countries calculated by the index III based on the W^C weighting with the ranking of these countries in other e-readiness indices similar to the index III. The first index is Networked Readiness Index (NRI) for the year 2019, which covers 121 countries and consists of 53 indicators grouped into four categories: Technology, Citizens, Governance and Impact [25].

The second index is Artificial Intelligence Readiness (AIR) for the year 2019. The index AIR covers 194 countries and is made up of 11 indicators divided into four categories: Governance, Infrastructure and data, Skills and education, Government and public services [26]. Both NRI and AIR indices use fair weighting to calculate the final country score. Table X lists the six countries with the largest ranking difference $\boldsymbol{Rank^{sw}} - \boldsymbol{Rank^{cw}}$ and their ranking in the three indices: III, NRI and AIR.

Table X: Comparison between the classification of indices III, NRI and AIR for the six countries

Country	$Rank^{SW}$	$Rank^{CW}$	$Rank^{SW} - Rank^{CW}$	Rank NRI	Rank AIR
Netherlands	29	15	14	3	14
Switzerland	14	4	10	5	18
Czech Rep.	41	31	10	30	31
Poland	11	21	−10	37	27
Chile	16	26	−10	42	39
Russia	19	29	−10	48	29

We note that despite the great difference in ranking of score $\boldsymbol{Rank^{SW}} - \boldsymbol{Rank^{CW}}$ for the six countries, their $\boldsymbol{Rank^{CW}}$rankings remain reasonable in comparison with their rankings in the NRI and AIR indices. Indeed, the classification of Netherlands went from position 29 in the W^S weighting to position 15 in the W^C. This is a reasonable improvement since Netherlands is ranked 3 out of 121 countries in the NRI index and 14 out of 194 countries in the AIR index. By the same reasoning, the classification of Poland is degraded from position 16 in the W^S weighting to position 26 in the W^C. This is a reasonable deterioration since Poland is ranked 37 in the NRI index and 27 in the AIR index.

The use of the combined weighting between W^O and W^S in the calculation of the index III of the year 2019 shows that the objective weighting based on the measure of importance of the indicators using the random forest algorithm makes it possible to effectively adjust the subjective weighting given by the designer of the index in order to build a single global and complete weighting.

VI. CONCLUSION

E-readiness assessment is becoming an essential tool for governments. It allows decision makers to track the use and impact of information and communication technologies (ICT)on growth and economic development. This tool is developed by several worldwide organizations to provide a comprehensive index calculated by the composite indicator approach from a selection of weighted indicators. Indeed, each indicator is characterized by a weight that reflects its importance and priority in the index evaluation. However, the weighting systems used by the majority of organizations for the e-readiness assessment are based on a single objective or subjective method. Indeed, there are two approaches in the weighting systems: (a) subjective weighting designed from a set of expert opinions in the evaluation area and which only depends on the judgments of the designer of the index. (b) objective weighting based on a statistical method applied to the evaluation data and which only depends on the characteristics of the data. To remedy this problem, we have proposed in this article two contributions: (1) proposal of a new complete weighting system by the combination of objective weighting and subjective weighting; and (2) development of a new method to calculate objective weighting based on the measure of the indicator importance using the random forest algorithm. This approach makes it possible to exploit the complementarily of the two objective and subjective weightings to increase the precision of importance of each indicator by taking into consideration the properties of the data and the relation of influence between indicators on the one hand, and the priority of each indicator given by a set of experts opinion on the other hand.

As a case study, the approach was applied to the Inclusive Internet Index III of the year 2019, which allowed us to compare the difference between the subjective weighting used by the EIU in the calculation of the index III and the combined weighting calculated by a combination of objective and subjective weightings. The difference between the two rankings based on the subjective weighting and the combination weighting of the 100 countries experienced an absolute average difference of 2.94. The correlation between the two scores is 0.994. In addition, the new rank of countries according to the III score based on the combined weighting remains reasonable in comparison to other indices similar to III, such as NRI and AIR.

The objective of this article is to exploit the variable importance method using the random forest algorithm to calculate the objective weighting and to combine it with the subjective weighting to build a complete weighting system. Inspired by this approach, future research on objective weighting aims to exploit other algorithms apart from random forests to measure the importance of indicators in order to improve objective weighting.

APPENDIX

Table XI: Results of scores of the 100 countries ranked according to the score III^{cw}in comparison toIII^{sw}

Pays	III^{sw}	$Rank^{sw}$	III^{cw}	$Rank^{cw}$	Difference $Rank^{sw} - Rank^{cw}$
Netherlands	80.5	29	79.82	15	14
Switzerland	84.1	14	83.35	4	10
Poland	84.6	11	78.78	21	−10
Chile	83.4	16	77.18	26	−10
Russia	81.9	19	75.77	29	−10
Czech Republic	74.7	41	72.86	31	10
Colombia	76.1	35	69.68	44	−9
Italy	81.8	20	76.85	28	−8
China	74.3	42	72.3	34	8
UAE	74.2	43	72.03	35	8
India	73.2	47	64.67	55	−8
United States	86.3	3	81.9	9	−6
Taiwan	81.6	22	79.71	16	6
Belgium	81.4	25	78.96	19	6
Nigeria	64.8	65	55.87	71	−6
Finland	85.3	6	81.45	11	−5
Israel	82.8	17	78.37	22	−5
Qatar	75.5	37	72.76	32	5
Malaysia	76.2	34	71.39	39	−5
Uruguay	72.3	48	69.75	43	5
South Korea	85.1	9	83.14	5	4
Estonia	81.5	24	78.88	20	4
Romania	80.8	27	78.15	23	4
Hungary	80.7	28	78.15	24	4
Ukraine	78.3	32	72.01	36	−4
Argentina	78.2	33	71.77	37	−4
El Salvador	68.4	59	60.79	63	−4
Venezuela	56.9	78	53.83	74	4
Botswana	56.1	81	53.28	77	4
United Kingdom	85.4	5	82.44	8	−3
Portugal	84.2	13	81.48	10	3

Ireland	81.7	21	79.04	18	3
Austria	81.6	22	77.99	25	−3
Kazakhstan	71.9	50	68.22	47	3
Mexico	73.4	45	67.83	48	−3
Panama	70.2	55	65.84	52	3
Mongolia	70.7	53	64.58	56	−3
Indonesia	67.2	63	63.01	60	3
Jamaica	63.9	68	60.47	65	3
Nepal	60.9	72	53.73	75	−3
Pakistan	57.8	77	50.86	80	−3
Namibia	53.2	84	50.3	81	3
Tanzania	56.2	79	50.07	82	−3
Spain	85.2	8	82.97	6	2
France	84.9	10	81.38	12	−2
Brazil	79.7	31	72.5	33	−2
Thailand	75.7	36	71.52	38	−2
Kuwait	75.4	38	70.83	40	−2
Saudi Arabia	75.3	39	70.8	41	−2
Turkey	75	40	70.49	42	−2
Jordan	70.8	52	66.61	50	2
Iran	69.7	56	64.8	54	2
Peru	69.7	56	63.77	58	−2
Dominican Republic	67.9	61	63.36	59	2
Philippines	64.6	66	60.65	64	2
Kenya	67.1	64	59.98	66	−2
Egypt	63.5	69	58.66	67	2
Bangladesh	61.9	71	56.6	69	2
Myanmar	59.3	74	53.41	76	−2
Cameroon	58.1	76	52.41	78	−2
Angola	50.4	87	45.94	85	2
Mozambique	42.5	94	38.55	92	2
Mali	43.2	91	37.88	93	−2
Singapore	87.3	2	86.72	1	1
Sweden	89.5	1	86.23	2	−1
Denmark	85.9	4	83.6	3	1
Canada	85.3	6	82.45	7	−1
Japan	84.3	12	81.08	13	−1
Australia	83.6	15	79.92	14	1
Germany	82.7	18	79.64	17	1
Bulgaria	80.9	26	76.88	27	−1
Vietnam	73.7	44	68.91	45	−1
South Africa	71.9	50	66.4	51	−1
Ecuador	70.6	54	65.14	53	1
Sri Lanka	69.4	58	63.97	57	1
Tunisia	68	60	62.19	61	−1
Guatemala	64.3	67	57.9	68	−1
Algeria	59.6	73	54.95	72	1
Cambodia	59.3	74	53.86	73	1
Côte d'Ivoire	54.7	82	48.62	83	−1
Senegal	53.4	83	47.09	84	−1
Uganda	51.5	85	45.67	86	−1
Zambia	50.5	86	45.65	87	−1
Madagascar	43.1	92	39.65	91	1
Burkina Faso	43	93	37.36	94	−1
Greece	80.3	30	75.41	30	0
Costa Rica	73.3	46	68.28	46	0
Oman	72.2	49	67.78	49	0
Morocco	67.4	62	61.97	62	0
Ghana	62.8	70	56.51	70	0
Rwanda	56.2	79	51.02	79	0
Benin	48	88	42.38	88	0
Ethiopia	45.5	89	41	89	0
Sudan	44.8	90	40.7	90	0
Guinea	40.3	95	35.78	95	0
Liberia	38.5	96	35.06	96	0
Sierra Leone	38	97	34.22	97	0
Malawi	36.6	98	33.54	98	0
Niger	33	99	28.38	99	0
Congo DRC	29.3	100	26.47	100	0

REFERENCES

1. M. Nardo, M. Saisana, A. Saltelli, and S. Tarantola, 'Tools for composite indicators building', Eur. Com. Ispra, vol. 15, pp. 19–20, 2005.
2. P. Zhou, B.W. Ang, and K.L. Poh, 'A mathematical programming approach to constructing composite indicators', Ecol. Econ., vol. 62, no. 2, pp. 291–297, 2007.
3. L. Rabii and D. Abdelaziz, 'Comparison of e-readiness composite indicators', in 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA), 2015, pp. 93–97.
4. R.K. Singh, H.R. Murty, S.K. Gupta, and A.K. Dikshit, 'Development of composite sustainability performance index for steel industry', Ecol. Indic., vol. 7, no. 3, pp. 565–588, 2007.
5. S. Amiri and J.M. Woodside, 'Emerging markets: the impact of ICT on the economy and society', Digit. Policy Regul. Gov., vol. 19, no. 5, pp. 383–396, 2017.
6. S. Alsheibani, Y. Cheung, and C. Messom, 'Artificial intelligence adoption: AI-readiness at firm-level', Artif. Intell., vol. 6, pp. 26–2018, 1997.
7. N.L. Pollesch and V.H. Dale, 'Normalization in sustainability assessment: Methods and implications', Ecol. Econ., vol. 130, pp. 195–208, 2016.
8. W. Becker, M. Saisana, P. Paruolo, and I. Vandecasteele, 'Weights and importance in composite indicators: Closing the gap', Ecol. Indic., vol. 80, pp. 12–22, 2017.
9. [9] X. Gan et al., 'When to use what: Methods for weighting and aggregating sustainability indicators', Ecol. Indic., vol. 81, pp. 491–502, 2017.
10. F.-L. Yin, Y.-Y. Wang, L. Lu, and D.E.S. No, 'Research on a combination weighting method of broadcasting and television program evaluation', J. Comput., vol. 28, no. 6, pp. 171–183, 2017.
11. L. Hongjiu and H. Yanrong, 'An evaluating method with combined assigning-weight based on maximizing variance', Sci. Program., vol. 2015, p. 3, 2015.
12. M. Alemi-Ardakani, A. S. Milani, S. Yannacopoulos, and G. Shokouhi, 'On the effect of subjective, objective and combinative weighting in multiple criteria decision making: A case study on impact optimization of composites', Expert Syst. Appl., vol. 46, pp. 426–438, 2016.
13. H. Zhang, P. Ji, J. Wang, and X. Chen, 'An improved weighted correlation coefficient based on integrated weight for interval neutrosophic sets and its application in multi-criteria decision-making problems', Int. J. Comput. Intell. Syst., vol. 8, no. 6, pp. 1027–1043, 2015.
14. J. Chennouf and N. Belkhayat, 'E-readinesscompositeindicatorsmeasurementmethodologies: Literaturereview', E-Soc. 2018, pp. 330–334.
15. U. Grömping, 'Variable importance assessment in regression: linear regression versus random forest', Am. Stat., vol. 63, no. 4, pp. 308–319, 2009.
16. P. Wei, Z. Lu, and J. Song, 'Variable importance analysis: a comprehensive review', Reliab. Eng. Syst. Saf., vol. 142, pp. 399–432, 2015.
17. L. L. Nathans, F. L. Oswald, and K. Nimon, 'Interpreting multiple linear regression: A guidebook of variable importance', Pract. Assess. Res. Eval., vol. 17, no. 9, 2012.
18. [18] C. Strobl, A.-L. Boulesteix, A. Zeileis, and T. Hothorn, 'Bias in random forest variable importance measures: Illustrations, sources and a solution', BMC Bioinformatics, vol. 8, no. 1, p. 25, 2007.
19. L. Breiman, 'Random forests',Mach.Learn.,vol. 45,pp. 5–32, 2001.
20. B. Gregorutti, B. Michel, and P. Saint-Pierre, 'Correlation and variable importance in random forests', Stat. Comput., vol. 27, no. 3, pp. 659–678, 2017.
21. Y. Xu and Z. Cai, 'Standard deviation method for determining the weights of group multiple attribute decision making under uncertain linguistic environment', in 2008 7th World Congress on Intelligent Control and Automation, 2008, pp. 8311–8316.
22. D. Sun, Y. Jia, L. Qin, Y. Yang, and J. Zhang, 'A variance maximization based weight optimization method for railway transportation safety performance measurement', Sustainability, vol. 10, no. 8, art. 2903, 2018.
23. The Economist Intelligence Unit, 'The Inclusive Internet Index 2019 Methodology Report'. [Online]. Available: https://theinclusiveinternet.eiu.com/assets/external/downloads/3i-executive-summary.pdf. [Accessed: 20-Nov-2019].
24. The EIU, 'Inclusive Internet Index Data 2019'. 2019.
25. D. Soumitra and L. Bruno, 'The Network Readiness Index 2019', 2019. [Online]. Available: https://networkreadinessindex.org/wp-content/uploads/2019/12/The-Network-Readiness-Index-2019.pdf. [Accessed: 14-Jan-2020].
26. I. Oxford and IDRC, 'Government AI readiness index 2019', 2019. [Online]. Available: https://ai4d.ai/wp-content/uploads/2019/05/ai-gov-readiness-report_v08.pdf. [Accessed: 14-Jan-2020].

AUTHORS PROFILE

Rabii Lamriq, Is A Research Student At Med V University Of Rabat, Morocco. His Research Is Focused In Ict Readiness And E-Strategy. As A Data Scientist With 10 Years Of Experience In Machine Learning And Big Data Analytics, Lamriq Is Interested In Machine Learning Algorithms And Their Use In E-Readiness Assessment Methodologies.

Najib Belkhayat, holds a PhD in computer sciences specialized in digitalization and e-strategies. Pr. Belkhayat is professor-researcher at ENCGM (business school of UCA-Marrakech) interested in e-Strategy, Digitalization and IS Governance and Management disciplines. Pr. Belkhayat have been Information Systems Manager and conducts consultancy missions for digitalization and IS strategy for Moroccan companies.

Pr. Abdelaziz Sdigui Doukkali, is a Professor of Higher Education, he has a Doctorate in Engineering Sciences from the National Institute of Telecommunications, Univ. Paris XII. His research topics are: Semantic search engines; Meta search engines; Arabic language processing; E-Strategy.