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Evaluation of Indicators for ICT Development Index using an Integrated Entropy Weighting Method

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Abstract

The ICT Development Index (IDI) is an established tool which is used for measuring the digital divide and facilitating the comparison of ICT performance within and between countries. Information entropy, which reflects the level of uncertainty in a random variable, can be applied to a range of fields, including information and communication technology (ICT). When designing a data analysis using information entropy, metrics derived from this method must be observed, evaluated, and utilized. The methodology proposed aims to assign weights to the indicators within the ICT development index and sub-indexes, enabling their global, regional, and country-wise ranking. To test the effectiveness of this methodology, we examined its potential applications for evaluating indexes. Our model integrates a novel approach that combines the entropy weight coefficient method, bootstrap method, correlation coefficient weighting method, and S-shaped diffusion stages of ICT. We present the evaluation results of the integrated calculation method.

Keywords: ICT indicators, entropy weight, IDI, IESC

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1. INTRODUCTION

The International Telecommunications Union (ITU) has published the IDI annually since 2009. The IDI is a valuable tool for policymakers and researchers to evaluate the effectiveness of policies and initiatives aimed at promoting ICT development, benchmarking progress, and sharing best practices among countries [1], [2]. It provides an objective assessment of international performance based on quantitative metrics and benchmarks. The IDI's measurement of ICT growth and progress at an international level is an essential tool for decision-makers [2], [3]. The IDI captures the evolution of the information society across various stages of development, including ICT readiness, use, capacity, and effect [4]. It also recognizes the convergence of technology and the emergence of new technologies, making it an effective tool for assessing the impact of ICT on society and the economy.

The IDI is made up of three sub-indexes, which are the access sub-index, the usage sub-index, and the skills sub-index. The weight assigned to each sub-index in the calculation of IDI is determined based on the results of the study of the main components [5]–[7]. The access and usage sub-indexes each account for 40% of the total weight, while the skills sub-index is assigned a weight of 20% since it is based on indicators. It is important to optimize the percentages of ICT indicators in the IDI sub-index and the percentages sub-index in the IDI [5]. In 2017, the ITU's World Telecommunications Statistics Indicators Symposium issued a resolution on the IDI, which defines the ICT rates globally and provides support for countries current rapid growth [6]. In 2019, the IDI calculation included 14 indicators, with two indexes removed from the 11 indicators previously used to form the three sub-indexes of access, usage, and skills. The ITU recommended that the IDI for 2019 be published based on the methodology and set of indicators instead of publishing it in any way [7]. As a result, data from IDI 2017 and previous years were used.

The paper is structured as follows: Section 2 reviews related works. Section 3 presents the methodology for evaluating the index, including the weighting methods and the proposed Integrated Entropy Weighting Method (IESC) methodology. In Section 3, the efficacy of the presented proposed combined method that utilizes weighing methods is demonstrated by presenting the results and a case study, highlighting its applicability. The IESC methodology and the results are also discussed. Finally, Section 4 concludes the study.

2. RELATED WORKS

ICT is causing significant and far-reaching transformations in various aspects of social and economic activity, with the adoption of this technology typically following an S-curve as per the predictions of the diffusion of innovations theory [8], [9] and can also be employed in a non-mathematical way to observe the stages of other technological phenomena [10]–[12]. In the context of the IDI, indicators are based on the S-shaped diffusion model, which encompasses impact, intensity, and readiness stages [8].

Multi-criteria decision-making (MCDM) methods are commonly used to determine the priority of various performance indicators of a system [13]–[15]. Popular MCDM methods include a technique for order preference by similarity to an ideal solution (TOPSIS) [13]–[15], gray theory [16], fuzzy method [17], analytic hierarchy process (AHP) [18], [19], and entropy-based method [20]–[30], among others. Integrating different MCDM methods can result in combined benefits [13], [14], [31]–[34]. Gray system theory is frequently used in decision-making and comprehensive evaluation problems due to its ability to provide an unbiased estimate of the unknown system's behavior, even with limited data [16], [30], [35], [36]. Index values may differ for decision-makers during the detailed evaluation process, and various techniques have been used to obtain index weights, such as subjective, objective, and hybrid techniques. AHP is a powerful tool for building complex and generally irreversible solutions, thanks to its ability to decompose complex problems into layers and quantitatively handle multi-criteria systems. The entropy-based method is a widely used objective weighted method but does not take into account the interrelationships between criteria. Other weighting methods, such as weighing method integrating correlation coefficient and standard deviation (CCSD) [37] and criteria importance through inter-criteria correlation (CRITIC) [38], incorporate the correlation coefficient (CC) [38], [39] of metrics from a different viewpoint. Subjective weighting methods can produce significantly different index weightings [29], [36],

[38], [40], making it essential to conduct a weight analysis that provides detailed, quantifiable research of weight.

The aim of this study is to propose an approach for sub-index weighting in the assessment of the IDI, taking into consideration the parameters of ICT indicators. The combination of weights can compromise the objective weights, so the proposed approach is the IESC, which incorporates the bootstrap method [41], the S-shaped diffusion stages of ICT, the entropy weighting method, and the CC weighting method.

3. INDEX EVALUATION METHODOLOGY

In this section, we will present the development of an integrated evaluation model for the IDI. The following subsection will provide an overview of several key theories, followed by a detailed explanation of the proposed integrated algorithm.

3.1. Entropy weighting method

The concept of information entropy measures the amount of information that can be obtained from a source of random data. It was introduced by Shannon [21]–[28]. The measurement unit depends on the logarithm base used, and entropy can be used to quantify factors such as system disorder, unequal distribution, degree of dependence, or complexity [23]. Entropy is originally a thermodynamic principle used to explain an irreversible process in a moving state and is later used to quantify the uncertainty in knowledge-related things. The entropy weighting method is used to compute index values under objective conditions, improving the objectivity of rank lists and reducing the subjectivity of weight assignment [25], [30]. The entropy weighing method is a procedure of calculating the index values of analyses under objective conditions, which may evaluate intent and degree of order and efficiency, attributing to entropy estimation of the information. The entropy weighting approach enhances the objectivity of rank lists [22], [27], [28]. This approach reduces the subjectivity of the weight assigned to various parameters, resulting in assessment results that better reflect the actual situation. The entropy weight is defined by judgment matrices, with more available information resulting in less entropy. The weight assessment process involves formulating alternatives and evaluation index and deriving the entropy weight using Shannon's entropy theory [27], [32]–[36]. The following are the specific steps:

1) Assuming that there are m additional elements that require measurement, and we have an algorithm for measuring n objects, we must create an evaluation matrix for the evaluation model.

$$X_{ij} = \left(x_{ij}\right)_{mxn} \tag{1}$$

The notation x_{ij} represents the elements of a matrix, while the value of the i^{th} indicator of the j^{th} the sample is denoted as x_{ij}.

2) The matrix needs to be normalized using the following operations:

$$d_{ij} = \frac{x_{ij}}{\max x_{ij}} \tag{2}$$

The resulting normalization matrix is obtained as follows:

$$D_{ij} = \left(d_{ij}\right)_{mxn} \tag{3}$$

3) The related weight of x_{ij} is:

$$P_{ij} = \left(p_{ij}\right)_{mxn}$$
$$p_{ij} = {d_{ij}}\Big/{\sum_{i=1}^{m} d_{ij}} \tag{4}$$

4) Equation (5) represents Shannon's information entropy for the i^{th} indicator of the matrix, where m is the number of indicators and n is the number of objects.

$$E_i = -\frac{1}{\ln(n)}\sum_{j=1}^{n} p_{ij}\ln p_{ij} \tag{5}$$

To standardize the value of E_i and ensure that $0 < E_i < 1$.

5) The equation for representing the entropy weight is given below:

$$w_i = \frac{1 - E_i}{m - \sum_{i=1}^{m} E_i} \tag{6}$$

The equations (1)–(6) are frequently used to compute the entropy weights using the measurements. Nevertheless, the assumption of independent probability for the ICT indicators may not hold true as they could be interrelated and affect each other at varying levels of ICT progress.

3.2. The diffusion stages of ICTs

Accurately and cost-effectively assessing ICT can help measure its impact on other developmental factors in a country, such as technical preparedness and economic growth [8]. The distribution of ICT in a country is typically divided into the following three stages:

1) Stage 1 – ICT readiness: When a country or region encounters a new technology, the readiness of its people to adopt it becomes a pivotal matter. It is essential to implement related measures that encompass the preparedness of businesses, infrastructure, and the overall economy of the country to embrace new technology.
2) Stage 2 – ICT intensity: As countries continue to adopt ICT, the significance of their usage intensifies in various ICT-related entities. Measuring ICT diffusion plays a crucial role when ICTs are widespread in a country or region but lack the capability to fully cover the entire population, leading to the notion of a digital divide.
3) Stage 3 – Impact: At this stage, the implementation activities on national-level economic and business activities and the effects of ICT investment are assessed. It includes evaluating how ICT-related development is affecting the economy and exploring whether the impacts are generating potential benefits, which is especially important for developed countries.

This stages model enables to assess and prioritize the diverse measurement requirements for ICTs. The adoption of ICTs between countries is influenced by the underlying infrastructure conditions that affect the level of digitalization intensity. The third dimension, which pertains to changes in social and economic structures, is still in its early stages, making research in this area potentially misleading [9]. As a result, we prioritize readiness indicators over digitalization and impact indicators. Since it is challenging to define the exact metric values at each stage of ICT adoption, non-parametric statistics such as ranks are more appropriate to use instead of numerical values [10], [12]. The non-parametric statistics are used when a population does not conform to any parameterized distributions [11], and they are commonly applied to ranked populations [10]. The non-parametric statistics have been used in this situation due to non-existing quantitative volumes of available variables, which would provide awareness of their specific distribution of data.

Figure 1 shows the stages of ICT diffusion. We assigned a higher rank to indicators of readiness and the lowest rank to indicators of exposure levels. The weight coefficients of ICT indicators determine by ICT diffusion in the three stages S-shaped form.

Readiness: designing the requisite technological, social, and commercial infrastructure to enable digitization. The readiness indicator enables every country to collect a statistical image of the infrastructure accessibility status required for digital digitization.

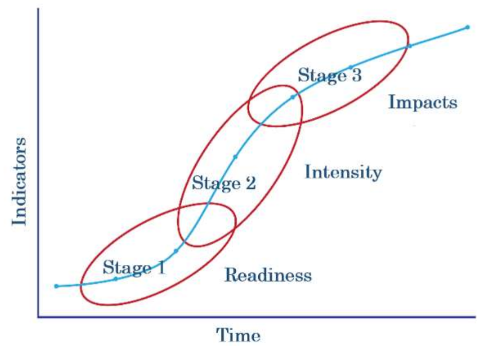

Figure 1. *The stages of ICT diffusion.*

Intensity: value, nature, and volume ICTs usage. Indicators of intensity enable countries to profile who exploits ICT and who doesn't. In addition, these indicators identify key applications and sectors.

Impact: value attached, theoretically generated by ICT. Statistics are necessary to determine either ICTs are making a difference when it comes to productivity and/or the development of new wealth sources. The indicators weights of IDI based on diffusion of an S-shaped curve with the readiness, intensity, and impact levels shown in Figure 1.

Meaningful connectivity necessitates robust infrastructure that is not only established and operational but also facilitates a swift and dependable connection. The framework embraces a technology-neutral approach, acknowledging the potential contributions of satellite connectivity, as well as fixed and mobile terrestrial networks [42], in connecting people to the internet.

3.3. Correlation coefficient weighting method

The Pearson CC [27], [37], [41] between the statistics of indicators f_i in the evaluation, statistics can be calculated using Equation (7). This results in a symmetrical matrix of size mxm with a generic element denoted by r_{ik} in a matrix of R. To determine r_{ik}, follow the steps below:

$$r_{ik} = \frac{n\sum x_{ij}y_{ik} - (\sum x_{ij})(\sum y_{ik})}{\sqrt{n\sum x_{ij}^2 - (\sum x_{ij})^2} \cdot \sqrt{n\sum y_{ik}^2 - (\sum y_{ik})^2}} \quad (7)$$
$$i, k = 1, 2, \dots, m$$

The symmetric matrix must be used to determine the correlation coefficient.

$$R = (r_{ik})_{mxm} \quad (8)$$
$$i, k = 1, 2, \dots, m$$

We utilize the sum function to estimate the level of disagreement caused by the index function f_i in comparison to the other indexes. This implies that the alternatives with higher discordant scores on criteria f_i and f_k should receive a lower r_{ik} rating. The sum vector can be normalized to obtain the weight of the CC:

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$$W_{ci} = \frac{\sum_{k=1}^{m}(1 - r_{ik})}{\sum_{i=1}^{m}\sum_{k=1}^{m}(1 - r_{ik})} \qquad (9)$$
$$i = 1, 2, \dots, m$$

CC weight W_{CC} can be obtained with Equation (9).

3.4. Proposed integrated entropy weighting method

This subsection aims to provide a detailed description of the proposed IESC integration algorithm. The estimation parameters for the entropy, ICT diffusion stages, and CC are set in the entropy resample matrices (see 3.1), ICT diffusion stages (see 3.2), and CC (see 3.3) weights with dimensions of $B \times m$, respectively.

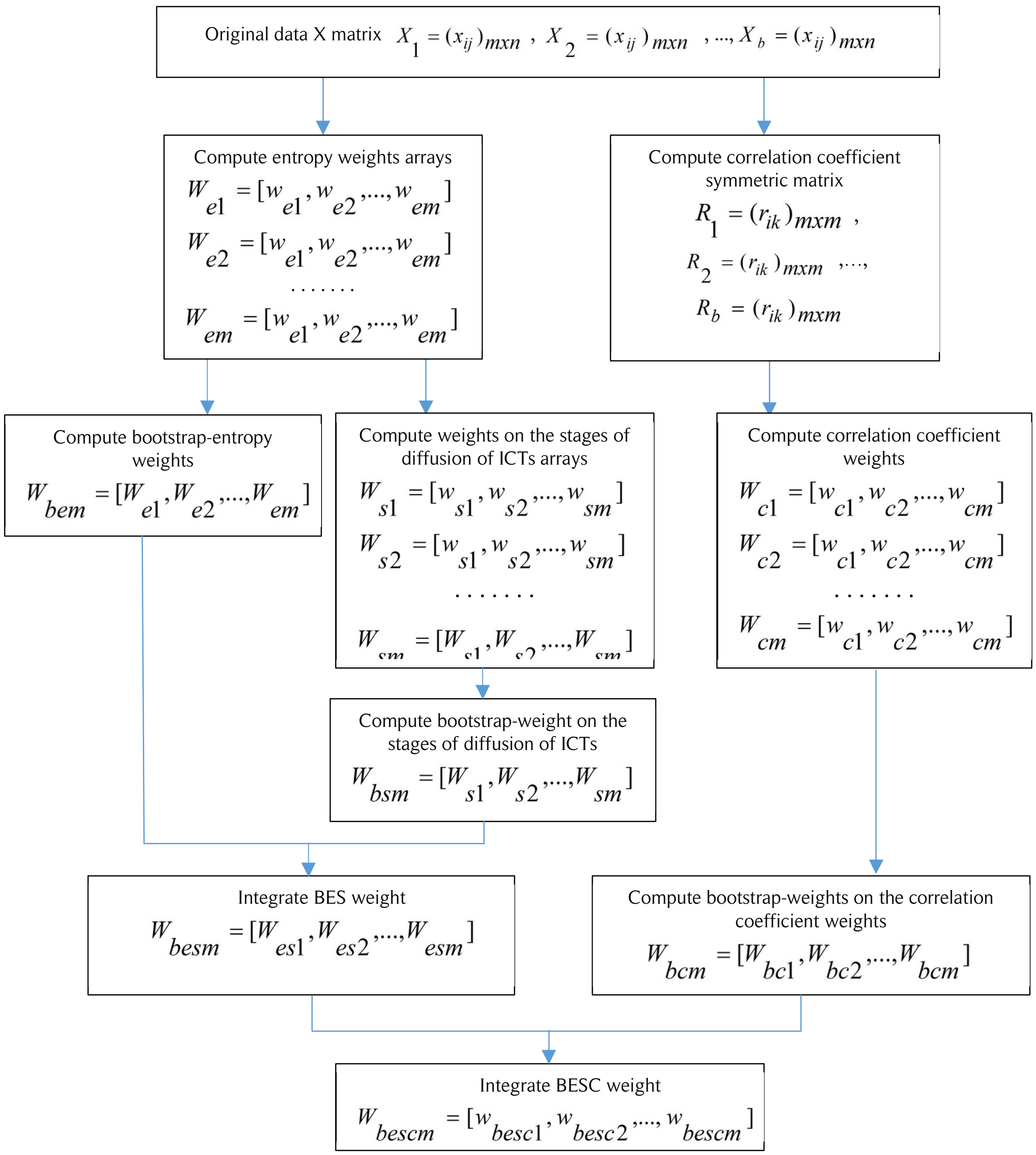

Figure 2. *Steps of the IESC weight calculation of our proposed algorithm.*

In other words, new weight vectors of W_e W_s and W_c are calculated at each resample time (years, months). Then, the bootstraps of entropy weights, ICT diffusion stages, and CC weights are represented as W_{be}, W_{bs} and W_{bc} respectively, can be obtained through an averaging result, which is formulated as follows:

$$W_{bei} = \frac{\sum_{b=1}^{B} {W_{bei}}/{B}}{\sum_{i=1}^{m} \left(\sum_{b=1}^{B} {W_{bei}}/{B}\right)} \tag{10}$$

To determine the weight W_{be}, employ the outcomes calculated by Equation (6).

$$W_{bsi} = \frac{\sum_{b=1}^{B} {W_{bsi}}/{B}}{\sum_{i=1}^{m} \left(\sum_{b=1}^{B} {W_{bsi}}/{B}\right)} \tag{11}$$

To calculate the weight W_{bs} by using the Stages of ICT S-shaped diffusion and applying the formula specified in Equation (11).

$$W_{bci} = \frac{\sum_{b=1}^{B} {W_{bci}}/{B}}{\sum_{i=1}^{m} \left(\sum_{b=1}^{B} {W_{bci}}/{B}\right)} \tag{12}$$

To find the weight W_{bc} by utilizing the output of Equation (9) and performing the calculation indicated in Equation (12).

$$W_{besi} = \frac{W_{bei} \cdot W_{bsi}}{\sum_{i=1}^{m} W_{bei} \cdot W_{bsi}} \tag{13}$$

To calculate the weight W_{bes}, apply the equation specified in Equation (13) using the results obtained from Equations (10) and (11). Similarly, to determine the weight W_{iesc}, use the results from Equations (12) and (13) and apply the calculation specified in Equation (14).

$$W_{iesc} = \frac{W_{besi} \cdot W_{bci}}{\sum_{i=1}^{m} W_{besi} \cdot W_{bci}} \tag{14}$$

The weight calculation algorithm for IESC is illustrated in Figure 2. The entropy theory is a valuable tool for assessing the uncertainty of data and considering the relationships between variables. When evaluating ICTs, appropriate, reliable, meaningful, and cost-effective measures should be used to determine their impact on other factors, such as technical preparedness and economic growth for advancing to subsequent stages. At the national level, there are three stages of ICT dissemination. The IESC method employs the bootstrap approach and the CC weight method based on the entropy principle.

4. CASE REVIEW OF ICT DEVELOPMENT INDEX INDICATOR

4.1. ICT development index

This section provides a detailed examination of the ITU IDI data from various regions worldwide [2]-[5]. The IDI comprises three sub-indexes: the access sub-index, the usage sub-index, and the abilities sub-index. The weighting assigned to each sub-index in the computation of IDI is determined through a study of the ICT indicators. The IDI aims to capture global trends in ICT development across countries that exhibit varying rates of growth. It employs a limited set of data that can be reliably collected from each country at all stages of development. Understanding the conceptual significance of the IDI is critical in recognizing that ICTs can facilitate development [6], [7]. The IDI report published by ITU provides a worldwide classification of regions, covering a total of 176 countries. The Asia-Pacific region comprises 34 countries, the Commonwealth of Independent States (CIS) includes 10 countries, the American continent consists of 35 countries, the Arab continent encompasses 19 countries, the European continent comprises 40 countries, and the African

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continent includes 38 countries. The study incorporates IDI indicator's data for all 176 countries by years.

4.2. The results of weights IDI indicators

The integrated model described in Section 3.4 was used for the comprehensive evaluation. Table 1 presents the weights for the indicators and sub-index of IDI, as well as the E, S, C, IESC weight index for global regions, and displays the weights obtained using the weighting methods of the decision matrix, including the four weights. To generate a new decision matrix, the access sub-index (consisting of ICT indicators A1, A2, A5, HH4, and HH6), the usage sub-index (encompassing ICT indicators HH7, A3, and A4), and the skills sub-index (comprising S1, S2, and S3) were considered. Table 2 provides a description of the ICT indicators used in the IDI.

TABLE 1
The weights of IDI indicators in sub-indexes

Region	Africa	Americas	Arab states	Asia Pacific	CIS	Europe	W_{be}	W_{bi}	W_{bc}	W_{iesc}
number of countries	38	35	19	34	10	40				
Access sub-index										
A1	0.121	0.184	0.194	0.077	0.171	0.129	0.1617	0.1788	0.1791	0.1613
A2	0.170	0.207	0.174	0.214	0.255	0.166	0.1958	0.1788	0.2036	0.1886
A5	0.225	0.145	0.195	0.210	0.143	0.140	0.2184	0.2154	0.1619	0.1977
HH4	0.237	0.233	0.219	0.246	0.256	0.283	0.2117	0.2117	0.2336	0.2280
HH6	0.247	0.231	0.218	0.254	0.175	0.281	0.2124	0.2154	0.2218	0.2244
Usage sub-index										
HH7	0.429	0.397	0.367	0.366	0.349	0.364	0.3576	0.3576	0.3536	0.3681
A3	0.219	0.250	0.305	0.307	0.323	0.340	0.2937	0.3212	0.3297	0.3060
A4	0.353	0.353	0.327	0.326	0.328	0.297	0.3487	0.3212	0.3167	0.3259
Skills sub-index										
S1	0.318	0.338	0.348	0.341	0.327	0.279	0.3379	0.3308	0.3536	0.3281
S2	0.356	0.347	0.349	0.346	0.373	0.391	0.3383	0.3383	0.3297	0.3493
S3	0.326	0.315	0.303	0.313	0.299	0.330	0.3238	0.3308	0.3167	0.3225
IDI sub-indexes										
Access sub-index	0.455	0.461	0.435	0.488	0.459	0.460	0.4508	0.4512	0.4190	0.4404
Usage sub-index	0.265	0.249	0.263	0.263	0.255	0.253	0.2720	0.2716	0.2426	0.2621
Skills sub-index	0.280	0.290	0.302	0.249	0.286	0.287	0.2772	0.2772	0.3383	0.2975

Table 2 and Figures 4-7 illustrate the percentage of differences in weight distribution of IDI indicators and sub-indexes between the ITU methodology and IESC, as well as the differences in each indicator and sub-index.

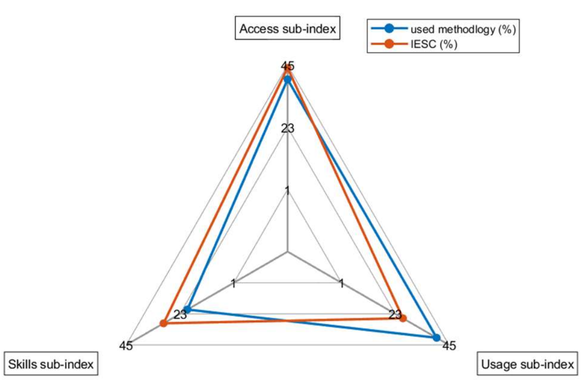

Figure 4. *Sub-indexes weight of IDI*

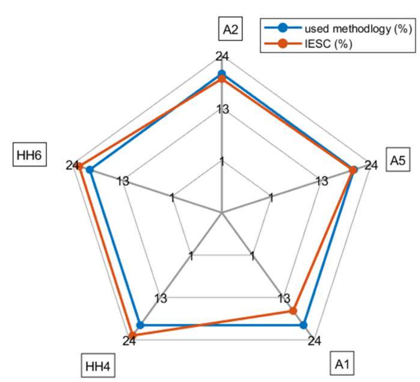

Figure 5. *ICT indicator weights of access sub-index*

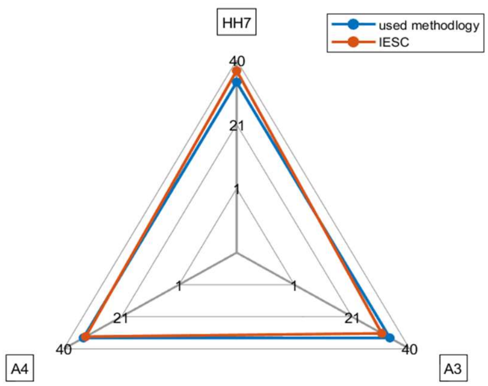

Figure 6. *ICT indicator weights of usage sub-index*

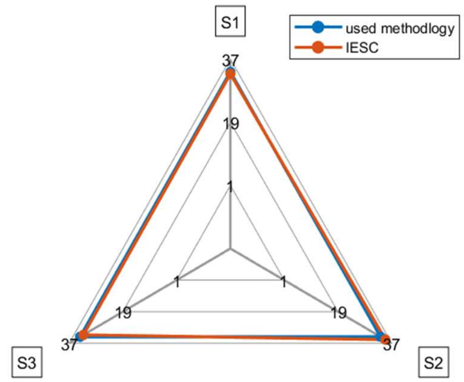

Figure 7. *ICT indicator weights of skills sub-index*

The results demonstrate a difference in indicators ranging from 0.23% to 3.87% in the access sub-index, 0.74% to 3.48% in the usage sub-index, and 0.52% to 1.6% in the skills sub-index.

TABLE 2

The percentages of differences in indicators and sub-indexes

IDI indicators	code	%	%	Difference indicators percentages	%	%	Difference sub-index percentages
Access sub-index							
Fixed-telephone subscriptions per 100 inhabitants	A1	20	16.13	3.87	40	44.04	4.04
Mobile-cellular telephone subscriptions per 100 inhabitants	A2	20	18.86	1.14			
International Internet bandwidth (bit/s) per Internet user	A5	20	19.77	0.23			
Percentage of households with a computer	HH4	20	22.80	-2.80			
Percentage of households with Internet access	HH6	20	22.44	-2.44			
Usage sub-index							
Percentage of individuals using the Internet	HH7	33.33	36.81	-3.48	40	26.21	13.79
Fixed-broadband subscriptions per 100 inhabitants	A3	33.33	30.60	2.73			
Active mobile-broadband subscriptions per 100 inhabitants	A4	33.33	32.59	0.74			
Skills sub-index							
Mean years of schooling rate	S1	33.33	32.81	0.52	20	29.75	-9.75
Secondary gross enrolment ratio	S2	33.33	34.93	-1.60			
Tertiary gross enrolment ratio	S3	33.33	32.25	1.08			

For the IDI sub-indexes, the difference ranges from 4.04% to 13.79%. Therefore, there is a need for optimization of the IDI indicators weights and reference values.

4.3. Ranking results of IDI indicators

The rankings of IDI indicators are presented in Table 3, based on both the ITU methodology and the proposed methodologies in this article in section 3. According to the ITU methodology, the A5 indicator has the highest rank, while the S2 and S3 indicators are ranked lower at the 10^{th} and 11^{th} positions, respectively. This table shows the IDI indicator coefficients computed by the ITU methodology, which incorporates reference values of indicators, sub-index weights, and weights of indicators within sub-indexes. The methodology assigns equal weights to the indicators within the sub-indexes and also equal weights to the sub-indexes in the IDI. By the ITU methodology, the A5 indicator holds the first position. The A1, HH7, and A4 indicators have the same score values, while the HH4 and HH6 indicators also have the same score values. However, according to the entropy weight coefficient method, the S2 indicator has the best performance, and A5 indicator is ranked 11th. Figure 8 shows the ranking of IDI indicators by weights of the IESC method.

The maximum weight coefficient value for the IDI indicator is 0.109, while the minimum weight coefficient is 0.077.

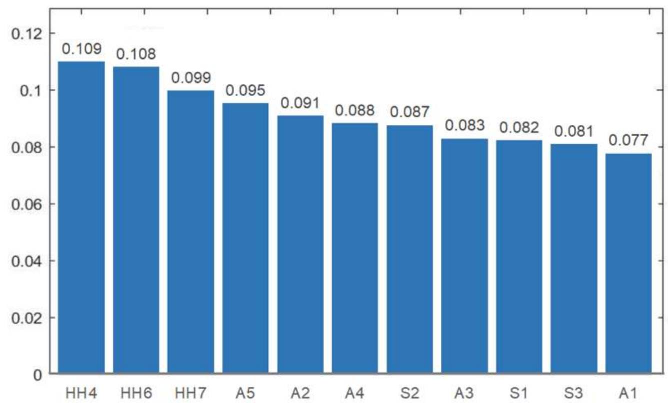

Figure 8. *Ranking IDI indicators by* W_{iesc}

The vectors of charts Figure 8 with linear trend line $y = -0.003x + 0.1099$ and $R^2 = 9422$ R squared value on the chart.

TABLE 3

The ranking and weight coefficients of evaluation values for indicators in IDI

IDI indicator	IDI indicator coefficient by ITU methodology	Rank	W_{iesc}	rank
A1	0.0133	3,4,5	0.0774	11
A2	0.0067	8	0.0905	5
A5	0.0982	1	0.0949	4
HH4	0.0080	6,7	0.1094	1
HH6	0.0080	6,7	0.1077	2
HH7	0.0133	3,4,5	0.0994	3
A3	0.0222	2	0.0826	8
A4	0.0133	3,4,5	0.0880	6
S1	0.0044	9	0.0820	9
S2	0.0007	10,11	0.0873	7
S3	0.0007	10,11	0.0806	10

The integrated weight is the most crucial aspect of the integrated method. W_{iesc} using Equation (14). Table 4 displays the weights of IDI sub-index indicators ranked by ICT indicator coefficients using the four methods discussed in this article, including the ITU methodology's ICT indicator coefficient with its corresponding percentages and sub-index indicator reference values.

TABLE 4

The Ranking and Weight Coefficients of Evaluation Values for Indicators in sub-indexes of IDI

IDI indicator	ICT indicator coefficient by ITU methodology	rank	W_{be}	rank	W_{bi}	rank	W_{bc}	rank	W_{iesc}	Rank
					Access sub-index					
A1	0.3333	1	0.1617	5	0.1788	4,5	0.1791	4	0.1613	5
A2	0.1667	5	0.1958	4	0.1788	4,5	0.2036	3	0.1886	4
A5	2.4547	2	0.2184	1	0.2154	1,2	0.1619	5	0.1977	3
HH4	0.2000	3,4	0.2117	3	0.2117	3	0.2336	1	0.228	1
HH6	0.2000	3,4	0.2124	2	0.2154	1,2	0.2218	2	0.2244	2
					Usage sub-index					
HH7	0.3333	2,3	0.3576	1	0.3576	1	0.3536	1	0.3681	1

A3	0.5556	1	0.2937	3	0.3212	2,3	0.3297	2	0.306	3
A4	0.3333	2,3	0.3487	2	0.3212	2,3	0.3167	3	0.3259	2
Skills sub-index										
S1	0.2222	1	0.3379	2	0.3308	2,3	0.3536	1	0.3281	2
S2	0.0333	2,3	0.3383	1	0.3383	1	0.3297	2	0.3493	1
S3	0.0333	2,3	0.3238	3	0.3308	2,3	0.3167	3	0.3225	3

The weight assigned to the A2 indicator in the access sub-index is 0.167, while the A5 indicator has a much higher weight of 2.45. As for the usage sub-index, the A3 indicator has a weight of 0.56, while both HH7 and A4 indicators share the same weight of 0.33. The weights for S2 and S3 indicators in the skills sub-index are both 0.033, while the weight for the S1 indicator is 0.22. When using the integrated method IESC, the results show that the weights for HH4 and A1 are first and fifth, respectively, in the access sub-index, and HH7 and A3 are first and third, respectively, in the usage sub-index. In the skills sub-index, the weight for S2 is first, and the weight for S3 is third.

5. CONCLUSIONS

This paper proposes an approach to evaluate the ranking of IDI for global regions and countries using eleven ICT indicators. An integrated weigh method is developed method is proposed on entropy-based method. Can obtain the following results:

The results of the evaluation can help to determine the appropriate ICT indicators for sub-indexes in IDI, as well as provide guidance on their respective weights and reference values within the IDI conceptual framework and methodology.

The integration of multiple established methods is proposed as an alternative approach to developing a comprehensive model. The combination includes the entropy-based entropy-weighted method, S-shaped diffusion of ICT development stages, weight CC method, and their integrated method. This approach aims to leverage the strengths of each method and overcome their limitations. The result indicates that combining the entropy weight method from information theory with distribution methods at different development stages is feasible for assessing ICT development indicators.

In addition to statistical calculation, our study demonstrates the potential of using information theory's entropy to calculate the ICT development index. The evaluation method employing entropy weighting offers a way to determine the overall value of the evaluation index system.

Results indicate the variations in indicators across different ranges: 0.23% to 3.87% in the access sub-index, 0.74% to 3.48% in the usage sub-index, and 0.52% to 1.6% in the skills sub-index. Moreover, the IDI sub-indexes exhibit a difference ranging from 4.04% to 13.79%. These findings highlight the necessity to optimize the weights and reference value of the IDI indicators.

Additionally, the weighted analysis introduced in this article can serve as a valuable instrument for fine-tuning the weights of IDI indicators. Furthermore, the methodology presented in this paper can be applied irrespective of any changes in the number or composition of indicators within the IDI sub-indexes.

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