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Evaluation of Digital Development Indexes Using MEREC and Hybrid MCDM Methods

Ivana Petkovski[1*] and Petar Vranić[1]

[1]Mathematical Institute of the Serbian Academy of Sciences and Arts, Belgrade, Serbia
[*]Correspondence: ivana993@turing.mi.sanu.ac.rs

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ABSTRACT

The use of relevant and structured instruments for measuring digital development is essential for policy-making in digitalization. The aim of the research is to compare structural adequacy of the global digital development indexes by means of multicriteria decision-making (MCDM). Theoretical contribution is to develop an evaluation framework and propose a novel methodological integration. Nine criteria were used to quantify six indexes: the Network Readiness Index (NRI), the E-Government Development Index (EGDI), the Digital Economy and Society Index (DESI), the ICT Development Index (IDI), the IMD World Digital Competitiveness Ranking (IMD) and the Global Digital Index (GDI). The criteria's objective weights were evaluated using the Method based on the Removal Effects of Criteria (MEREC) and the weights alterations effect was considered using the Shannon entropy method. The final prioritization was consolidated using five MCDMs scores: Combined Compromise Solution (CoCoSo), Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS), Additive Ratio Assessment (ARAS), COmbinative Distance-based ASsessment (CODAS) and Evaluation based on Distance from Average Solution (EDAS). Practical contribution and originality are presented by proposing first time evaluation framework of digital development indexes based on a recently proposed MEREC and selecting the most appropriate index (NRI) in a neutral MCDM context.

Keywords: Digital development, measurement frameworks, global digital indexes, multicriteria decision-making (MCDM), Method based on the Removal Effects of Criteria (MEREC), Combined Compromise Solution (CoCoSo), Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS), Additive Ratio Assessment (ARAS), COmbinative Distance-based ASsessment (CODAS), Evaluation based on Distance from Average Solution (EDAS)

1. Introduction

Providing a reliable and methodologically transparent measure of digital development of countries, despite a narrower or broader specialized scope, is a key tool for shaping the policy of digital progress (Bánhidi & Dobos, 2024). The existing literature offers a wide array of instruments for measuring digital development in the form of global indexes. The developed indexes (indices) were proposed by experts from world-renowned institutions in the field of technology such as Portulans Institute (PI), The Organization for Economic Co-operation and Development (OECD) and Huawei Technologies among others (Martínez et al., 2022; Huawei and IDC, 2024; Portulans Institute, 2024). Their availability greatly facilitates timely decision-making about digitalization matters. However, there are significant variations between them. The most frequent differences concern geographical coverage, alongside more significant ones such as the structure of indicators and the choice of ranking methodology (Siqueira et al., 2019; Sidorov & Senchenko, 2020). Such variability can lead to heterogeneity among the scores of various indexes and provide different rankings among the same countries or regions depending on the selected index. While this could offer a second opinion on the digitalization issue, it could also compromise the entire decision-making process and prioritization for policymakers or investors since their decisions often rely on a specific index and its rank list.

Special branch of indexes is focused on digital development like the European Commission's Digital Economy and Society Index (DESI), or the United Nations E-Government Development Index (EGDI). These indices have become strong steering tools that shape governments in diagnosing gaps, setting agendas, and justifies digital reforms. By reducing complex socio-technical systems into comparable metrics, they became a platform for inter-state benchmarking and “soft” competition, that can influence agenda setting and resource allocation (Davis et al., 2012; EC, n.d.; EC, 2024). In the European Union DESI has transitioned from an independent scorecard toward formal monitoring by integrating itself with the Digital Decade Policy Program as its monitoring mechanism. It transitions gradually from a “critical evaluation” scorecard to a formal monitoring functioning. DESI trajectories and annual assessments via States of the Digital Decade, concerning progress towards 2030 targets and country-specific recommendations issued to member states, allow for the raised interfacing of indicator movement with meaningful policy guidance and cooperative governance cycles (EC, 2024; 2025). In order to align national with regional development, such metrics are often internalized by national governments in their strategies. For instance, in 2017 Portugal lunched “National Digital Skills Initiative e.2030, (Portugal INCoDe.2030)”, an integrated public policy initiative, which aims to promote population's digital skills. According to INCoDe.2030, the plan is to consolidate the country's DESI standing, aligning investments in inclusion, skills, and research with the pillars of the scoreboard. Previous DESI country documentation also recorded the launch of INCoDe.2030 as a flagship strategy response to measured gaps (EC, 2018; International Trade Administration, 2024). Greece’s “Digital Transformation Strategy” and later “Digital Decade” roadmap similarly placed reforms on the agenda because of low DESI rankings - an example of how rankings can increase attention and EU Recovery funding on connectivity, skills, and digitalization of public services (HRMDG, 2019). Another example beyond Europe is for instance rapid improvements in UN EGDI standings promoted in the Saudi Vision 2030 documents and Digital Government Authority communications as evidence of reform momentum, thus using index movement as legitimacy for investment in digital identity, portals and service redesign (DGA, 2022; Vision 2030, 2025).

Several authors have used digital development indexes in different areas. Jovanović et al. (2018) and Imran et al. (2022) use DESI to evaluate sustainable development of European Union countries while Adams & Paul (2023) use EGDI with the same purpose however on the African countries sample. Sofrankova et al. (2025) employ DESI to investigate the relationship between population digital skills and digital development. Ishnazarov et al. (2021) and Magoutas et al. (2024) discussed the ICT index in the context of digital economy progress while Oloyede et al. (2023) performed a similar analysis while limiting the sample towards developing countries. On the other side, Sagarik (2023) studies the use of the IMD index in assessing national digital competitiveness. Kolat & Ünver (2025) propose the use of the ICT index to reflect the question of cybersecurity in terms of economic development. On the other side, Fernández-Portillo et al. (2020) use DESI to examine the impact of digital progress on the trend of economic growth while Tokmergenova & Dobos (2024) use NRI to provide technological clusters among the countries.

Besides its practical use, index structure also matters: for instance, the World Bank Digital Adoption Index (DAI) opened itself as an explicit tool to policy-makers in the design of context-enabled strategies across people, business, and government while the Network Readiness Index (NRI) calls itself a “compass” for governments navigating digital transformations-a deliberate theory of use encouraging policy uptake (World Bank, 2016; Portulans Institute, 2024). These examples illustrate to how indicators have been moving into the policy processes through benchmarking (to identify strengths/weaknesses), conditionality, and cooperation (to align with regional targets and support from donors), and signaling (to attract investment and talent through reputational gains). However, following the advice from science, these opportunities bring risks with them: 1) metric-driven governance could narrow the attention to what is measured, 2) may induce isomorphic “teaching to the test”, and 3) may end up hiding the contextual realities in situations with lower capacity. Responsible usage must come with combining quantitative dashboards with qualitative diagnostics and inclusive deliberation (Davis, et al., 2012a; Merry, 2016).

Gerpott & Ahmadi (2015) emphasize that when selecting an adequate index of digital development for their study, all existing indexes failed to be developed as measures that can be connected with the economic or social development of a country. Gerpott & Ahmadi (2015) state that most of the indexes have structural gaps such as relying on subjective weighting of the component’s importance. Therefore, a research gap exists in determining the most appropriate index in a neutral context at the macro level. At this point, a systematic framework for evaluating digital development index is missing. The multi-criteria decision-making methodology emerges as an adequate choice for solving this problem. In this case, the problem is to prioritize the Network Readiness Index (NRI), the E-Government Development Index (EGDI), the Digital Economy and Society Index (DESI), the ICT Development Index (IDI), the IMD World Digital Competitiveness Ranking (IMD) and the Global Digital Index (GDI) that serve as alternatives. The prioritization of the alternatives is performed across multiple criteria. The similar examples are given in studies by Stević et al. (2020), Huy et al. (2022) and Dudić et al. (2024). In addition to the possibility of applying a larger number of MCDM methods in the prioritization context, the applied data normalization method also plays an important role (Dudic et al., 2024). The proposed MCDM methodological framework in this paper provides an objective and stable approach to decision-making about the choice of instruments for measuring digital progress with the simultaneous integration of different, often conflicting criteria.

The research objective of this study is to critically evaluate the structural adequacy of global digital development indexes in order to determine their methodological validity, broadness and relevance by means of multi-criteria analysis. The main idea is to compare the indexes based on their characteristics and prove model robustness. This paper does not state that researchers or other decision-makers should exclusively use one index over the all others. It simply tries to develop a comprehensive framework for easier decision-making about the adequate index when various context-neutral criteria are considered such as geographical coverage, data normalization, multidimensional structure or frequent revision and others. Since this represents a general perspective, the combination of criteria and alternatives will change in respect to the decision-making context and goals.

The main goal will be achieved through four phases:

1. Identification of alternatives (indexes) and evaluation criteria to form a decision-making matrix and determine the objective criteria importance weights with MEREC methodology,
2. Index ranking using five multi-criteria methods to check the reliability of hybrid prioritization models,
3. Aggregation of ranks and evaluation of similarities and differences of the obtained ranks.
4. Evaluation of rank robustness with alternative weighting method.

The scientific contribution of the research is based on the analysis of the index structural adequacy or in other words - index structural characteristics, which improves the measurement methodologies and the proposal of standardized approaches when developing new indices. The results of the prioritization assist in the decision-making process of selecting the most suitable index through the evaluation of index advantages and limitations. The proposed methodological framework simplifies the choice between several indexes. In this paper, the MCDM context is neutral and does not reflect any specific decision-maker objective. It only serves to compare existing indexes. Within a practical use of this framework, the decision-maker should set a specific goal and priorities and afterwards assess the considered indexes. It supports the fact that the proposed model is flexible and can be adjusted to the user's needs. As a limitation of the study the authors agree that the index measurement precision and quality in the form of scores are out of the scope of this paper. This limitation is, for example, a research subject of authors Miškufová et al. (2025) who argue about the compliance between different ranking outcomes in digital competitiveness.

2. Literature Review

2.1. Digital development indexes

Although all digital indexes measure the digital progress of the world's economies, they are developed by different organizations and built on different methodologies.

The Network Readiness Index (NRI) is developed by the Portulans Institute in collaboration with partners such as Oxford University. The European Commission's Joint Research Centre - Competence Centre on Composite Indicators and Scoreboards audit NRI statistically to secure methodological thoroughness. The NRI (2024) is a composite that covers four main pillars: technology, people, governance, and impact, each with three sub-pillars. It comprises 54 indicators. For the construction of the index, primary objective data are used from renowned international sources. The index applies standard (min-max) normalization and employs equal weighting at each aggregation level. It tackles the digital divide by including both high- and low-income countries. The NRI specifically examines how countries utilize ICTs to enhance their competitiveness and overall development. It undergoes rigorous revision to suit the methodological updates and data availability. It is published annually. In the 2024 report, the index covers 133 countries, capturing a variety of economic development (95% of global GDP) (Portulans Institute, 2024).

The E-Government Development Index (EGDI) is published by the United Nations Department of Economic and Social Affairs (UN DESA). It is featured in its e-Government Survey. It focuses on three main pillars: provision of online services, telecommunication connectivity, and human capital, and thirteen sub-pillars with 191 indicators, if one counts every Online Service Index checklist item as an indicator. The survey reflects constructive improvements in the EGDI methodology, deriving from the lessons learned from previous editions. Each of the pillars is weighted equally and normalized by the Z-score method. The UNDESA irregularly revise EDGI indicators in respect to data availability and survey updates. Despite a stable core model, evolving technology and understanding shift the metrics' meanings, making the Survey a flexible comparative framework rather than a fixed linear path. It is developed on global survey frameworks and operationalized through consistent data sources, and it is released biannually. The report from 2024 covers 193 UN member states (UNDESA, 2022).

The ICT Development Index (IDI) is developed by the International Telecommunication Union (ITU). It is based on two main pillars: universal connectivity and meaningful connectivity, considering 11 indicators. The index values are normalized to a 0-100 scale by the min-max method. Methodology revisions are conducted roughly every four years following the ITU plenary processes. The index was suspended in 2018 and, after a methodology revision, was approved again in 2023 and a new edition is published in 2024. It regularly covers approximately 193 ITU member countries, but in 2024, 170 countries are considered, covering a wide spectrum of economies (ITU, 2024).

The Global Digitalization Index (GDI) is developed jointly by Huawei Technologies in collaboration with the International Data Corporation (IDC). It is built on four pillars: connectivity, digital platforms/foundation, sustainability/green energy, policy and ecosystem, and forty-two indicators normalized relative to defined targets. The data used are mostly objective data from bodies like ITU, WEF, UN, and World Bank acquired via Huawei and IDC measure frameworks. The index is published each year, with regular additions of indicators and country coverage to keep pace with digital transformation trends. It looked at seventy-seven countries constituting 93% of global GDP and 80% of world population at all development levels (Huawei and IDC, 2024).

The Digital Economy and Society Index (DESI) is developed by the European Commission to monitor the digital development of all EU Member States, covering diverse development levels. It is constructed of four equally weighted pillars: human capital, connectivity, technology integration and digital public services aggregated via simple weighted averages. It is organized through ten sub-pillars and a total of 32 indicators. The database is derived from Eurostat sources. DESI is press released annually and it is periodically updated (European Commission, 2022).

IMD World Digital Competitiveness Ranking (IMD) is an index that accumulates 59 criteria, where 38 belong to the hard data indicators and 21 survey responses. The structure is based on three main pillars: knowledge, technology and future readiness, assessed through 9 sub-pillars. Indicators are allocated balanced weights and normalized on scale from 0 to 100. IMD is published annually, with regular methodological updates that capture the digital transformation trend. It assesses 67 economies, covering a wide economic development range (IMD, 2024).

The Digital Government Index (DGI) is developed by the OECD. The DGI is constructed around six equally weighted pillar dimensions: digital by design, data-driven public sector, government as a platform, open by default, user-driven, and proactiveness, and thirty sub-pillars, evaluated through ninety-four questions covering each of the pillars. Data was drawn from a survey taken among senior government officials; thus, it considers a moderate degree of subjectivity. The DGI is published annually through the Government's at glance reports. Occasional changes are also being applied to the survey instrument and frameworks as well. The assessment includes 33 OECD member states, plus four accession countries (and sometimes partner regions), representing a range of economic contexts (OECD, 2023).

The Digital Adoption Index (DAI) is developed by World Bank. Data was published just once, in 2016, by the World Development Report of the World Bank, and has never been updated since. No further revisions have been made; hence, the data are now static. It covered roughly 180 countries across the whole economic spectrum. DAI is composed of three equally weighted sub-indices (people, government, business), each set of indicators built from objective supply-side data (World Bank, 2016).

Although similar in terms of general scopes, the indices differ significantly. Global-level annual composites such as NRI, EGDI, IDI, and GDI cover many economies based on a mix of infrastructure and skills, and governance are best for spotting gaps within the groups of income. Still, an equal rating of importance of components and normalization (min-max or z-scores) can all but mask crucial deficits, while OSI-style checklists tend to measure the service's availability and not its actual use or quality. Region or club-specific instruments (DESI for the EU; OECD's DGI) provide insights into public-sector capability but, by design, narrow variation-useful for benchmarking peers, less so for spotlighting extreme disparities. Survey-heavy indices (DGI; IMD's mix of hard data and executive opinions) can inject perception bias in a way that disfavors lower-income contexts. Methodology-wise, frequent revisions keep pace with tech but hinder comparability over time. In principle, an index linking access (connectivity, affordability, device quality) with capability (skills, data readiness) and outcomes (usage, impact) across wide sets of countries with as little subjective input as possible shall paint the clearest picture of the divide. There still needs to be subnational, gender, and affordability indices, which remain blind spots of most national-level dashboards (Sidorov & Senchenko, 2020).

As Davis et al. (2012) commented, various international rankings essentially attempt to simplify complex institutional and organizational profiles into a comparable metrics, to the extent digestible for media, politicians, or financial experts and investors. This way ranking systems can influence both external perception as well as definition of internal, national priorities. In this form, composite institutional characteristics or country scores are translated to understandable signals that can inform the allocation of investments, by explaining socio-economic and institutional qualities trough one standardized criterion; i.e., position on the ranking list can be turned into extent of foreign interests and investments (Groh et al., 2023).

The development of global indexes for measuring digital progress in the literature is addressed through multiple aspects that indicate their advantages but also numerous limitations.

2.2. Composite index considerations

Martínez et al. (2022) emphasize that the dimensionality and structure of the index are of crucial importance in the policy-making process because they contribute to a deeper understanding of the context and facilitate decision-making. This argumentation is supplemented by Lnenicka et al. (2022), who point out that the most common way of regulating index results is to alter the weight values of indicators or dimensions. When this strategy fails to yield the expected results, the structure itself must be changed. Such changes can lead to consistency problems making historical comparisons unfeasible. This challenge further complicates the position of developing countries, which are slower to implement new methodologies and lag behind developed countries in the preliminary reports.

The second important dimension of debate relates to the reliability and availability of datasets, as well as the index's universality. Sidorov and Senchenko (2020) show that common indexes such as NRI, EGDI and IDI do not offer universality in measurement because there is no complete database as a stable basis for their calculation. The authors propose an index derived from available data with the minimal presence of subjectivity in the calculations. Oloyede et al. (2023) offer a comparable view by discussing that the absence of a universal definition of the digitalization prevents the creation of comprehensive measuring instruments. The authors emphasize that databases from developing countries are often incomplete and inadequate, which makes analysis difficult. As one solution, Siqueira et al. (2019) use a dataset collected from a single source to develop a compatible index of digital development in enterprises. However, this approach has its limitations, since measuring once a year for a long period of time can be difficult because of the necessity to change indicators.

The third area of discussion concerns the way of assigning importance to certain indicators. Bánhidi and Dobos (2024) point out that assigning equal importance to indicators or dimensions, which are defined before data collection, is insufficient because it does not reflect the real informative value of the data. Instead, they propose that the significance weights should be based on the statistical characteristics of the set, which would increase the objectivity and precision of the measurement. These findings confirmed Denissova et al. (2025) who point to the problem of using outdated indicators that in the contemporary conditions fail to illuminate the level of digital development. The authors argue that such indicators do not allow measuring the disparities between urban and rural areas nor provide an assessment of important issues such as cyber security. As an alternative, it is proposed to introduce more modern measures, such as the level of automation. Further measures imply the simultaneous combination of subjective and objective indicators, which would ensure greater precision of the results and adaptability to the specific context.

Giovanni et al. (2005) note in their guide for creating an index in 10 steps that the accuracy of the data and their collection method are taken into account during the formation. In this regard, a controversy is placed on the surveying data because the correctness of the sample size and limitations must be analyzed. An additional dilemma is related to the data normalization because different methods yield different results. Those results can show sensitivity under extreme values or alteration of indicator weights. Then the principle of assigning weighting factors that directly affect the outcome is discussed. In that case, the authors suggest comparing the alignment of the obtained results with existing indices or indicators that measure the same or similar phenomenon. While Jiménez-Fernández et al. (2022) discuss the use of mathematical methods that enable the comparison of results within the index in a transparent manner. Greco et al. (2019) point out that the lack of differentiation in weights leads to confusion in the results. Certain indicators that are known to have a direct impact, while proven in the literature, can be neglected. Such an approach loses the informative value and introduces subjectivity because it is a planned developer choice. This effect is especially clear in the case when the value of collinear indicators is doubled, which is also agreed upon by the authors Jiménez-Fernández et al. (2022).

3. Research framework

The problem of selecting an index with the most appropriate structure is recognized in the literature (Gerpott & Ahmadi, 2015). Even though attempts to discuss and compare digital development indexes exist, the majority of relative studies such as Oloyede et al. (2023) or Chaonan et al. (2024) are limited to literature reviews. Buturac (2024) provides a qualitative assessment of the methodology, limitations and advantages. The study of Bai et al. (2024) argues the structure and multidimensionality of recently developed indexes and supports the role of MCDMs in developing novel indices. In practice, modern studies such as Chen & Wu (2022) or Liang & Tan (2024) rely on the MCDM framework for generating a composite index. However, none of these studies use or develop an evaluation framework in the form of a tool for prioritizing existing indexes. Therefore, this paper addresses the identified gap among studies and evaluates digitalization indexes based on multi-criteria analysis. The list of mostly used and evaluated indexes is presented in Table 1.

Index	Abbreviation	Publisher	First release	Latest release
Network Readiness Index	NRI	Portulans Institute (PI)	2002	2024
E-Government Development Index	EGDI	United Nations (UN)	2001	2024
The Digital Economy and Society Index	DESI	European Commission (EC)	2014	2024
The ICT Development Index	IDI	International Telecommunication Union (ITU)	2009	2025
Digital Government Index	DGI	The Organisation for Economic Co-operation and Development (OECD)	2019	2025
Digital Adoption Index	DAI	World Bank Group	2014	2016
IMD World Digital Competitiveness Ranking	IMD	IMD World Competitiveness Center	2017	2025
Global Digitalization Index	GDI	Huawei Technologies	2024	2024

Table 1. The common indexes for measuring digital development.

The research was divided into four phases, as illustrated in Figure 1:

Phase one. The evaluation of the criteria that express the structural adequacy of the most popular and latest global indexes of digital development is presented according to the established criteria in Table 2. The evaluation was performed using a recently reported MCDM method MEREC, adding to the objectivity of the analysis.

Phase two. The ranking of the digitalization indexes is performed. The ranking of indexes was realized using several MCDM methods with different methodological approaches to justify the stability of the results. In this procedure, newer methods in the literature introduced in the last decade such as CoCoSo, MARCOS, ARAS, CODAS and EDAS were used. These methods are used to show the ranking's reliability with the methods that have been confirmed in the last few years in the scientific literature.

Phase three. The result of the ranking presents an aggregated prioritization of indexes according to their structural adequacy and relevance. The overall prioritization was determined using the voting method, average absolute ranking differences and Spearman's correlation rank.

Phase four. The ranking's stability via the alternative weighting method is investigated. The authors use Shannon entropy to evaluate whether weight pounders have the capacity to modify rankings and how.

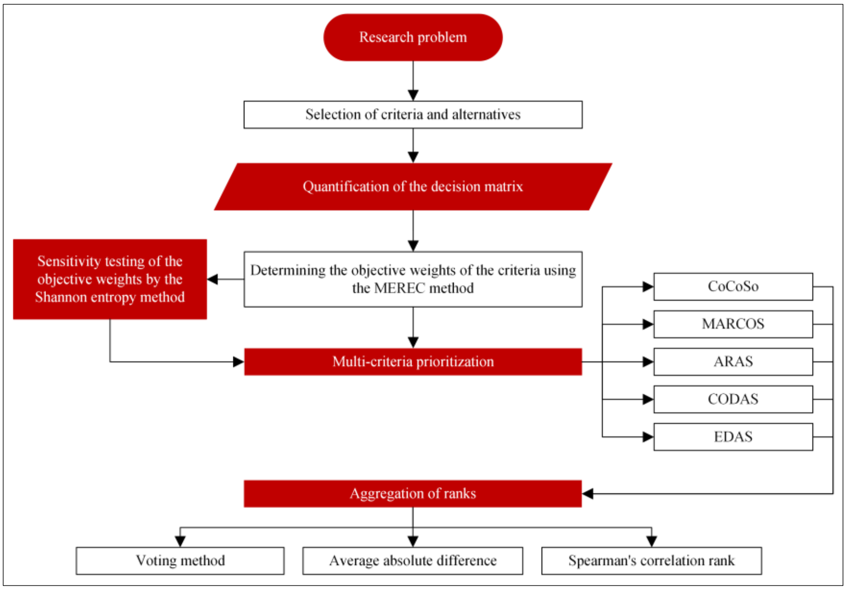

Figure 1. Research flow.

3.1. Multi-criteria decision-making framework

The preliminary review of the reports of world-renowned institutions in the field of digital development determined a large number of indexes, the basic information of which is shown in Table 1. The majority of reports are released for the year 2024, which was taken as the reference point. The DAI index and DGI index were eliminated from further research due to the lack of published report for 2024.

In this illustrative example the structural adequacy of the digitalization measurement indexes is evaluated based on a diverse criterion. The basic criteria with their definitions and qualitative and quantitative scales are shown in Table 2.

No	Criterion	Criterion definition	Qualitative scale	Quantitative scale
1	Geographic coverage (GC)	Number of countries included in the index.	High coverage > 100 countries	3
			Medium coverage of 50 - 100 countries	2
			Low coverage < 50 countries	1
2	Economic diversity of the sample (EDS)	Representation of countries of different levels of economic development.	Developed and developing countries	3
			Developing countries	2
			Developed countries	1
3	Number of indicators (NI)	The total number of indicators that make up the index.	Large number of indicators > 20 indicators	3
			Average number of indicators 10 - 20 indicators	2
			Small number of indicators < 10 indicators	1
4	Multidimensionality of the index (MI)	The number of dimensions that make up the index.	> 2 dimensions	3
			2 dimensions	2
			1 dimension	1

5	Coverage of the digital divide (CDD)	The coverage of the digital division that makes up the index.	3 dimensions of the digital divide	3
			2 dimensions of the digital divide	2
			1 dimension of the digital divide	1
6	Measurement approach (MA)	The degree of subjectivity of the data on which the index is based.	Objective measurements (government's official reports)	3
			Combined measurements	2
			Subjective measurements (expert assessments and surveys)	1
7	Data source (DS)	Data origin.	International and official sources	3
			Combined sources	2
			Private research and surveys	1
8	Normalization methodology (NM)	Application of some of the standard data normalization methods.	Standardized	3
			Partially documented	2
			Non-existent	1
9	Weighting method (WM)	Approach to determination of indicator weights.	Objective method	3
			Subjective method	2
			No weighting was applied	1
10	Publication frequency (PF)	Frequency of public release of index scores.	Regular publication = 1 year	3
			Periodic publication = 2 year	2
			Rare publication ≥ 3 years	1
11	Indicator update frequency (IUF)	Frequency of index indicator revision.	Periodic revision ≥ 2 years	3
			Regular revision = 1 per year	2
			No revision	1

Table 2. Common criteria for evaluating digitalization indexes.

Geographic coverage - the number of countries included in the assessment of digital development provides significant information about the applicability of the index outcome to different territorial contexts. Broader coverage allows for regional or global cluster analysis (Oloyede et al., 2023) and policy formulation targeting marginalized or digitally less developed areas (Giovanni et al., 2005).

Economic diversity of the sample - enables the evaluation of countries that are in different stages of economic development. In this way, digital progress is also observed through the influence of the economic disparities within the sample (Siqueira et al., 2019; Oloyede et al., 2023). This informs policymakers about the emerging economies' issues regarding further digital development and guides the allocation of financial resources toward lagging countries.

Number of indicators - affects the equilibrium of the results because an excessive number can burden the structure of the index and reduce the precision of measurement due to excessive variability. An insufficient quantity of data simplifies the structure and may lead to inaccurate results due to a lack of useful information (European Union & Joint Research Centre, 2008). A high quantity of indicators can mislead policymakers when developing strategies with excessive information.

Multidimensionality of the index - fluctuates according to the number of areas associated with digital progress (Sidorov & Senchenko, 2020; Martínez et al., 2022). If the index refers to a specific field, then it is specialized for measuring digital progress within that area, while covering a larger number of fields, the index remains valid for measuring digital progress at the macro-level. This is important if policymakers plan interventions across multiple sectors.

Coverage of the digital divide - certain aspects of the digital divide are often analyzed in the literature, which according to the standard definition of the author Van Dijk (2005) includes three levels. The level of access, the level of use and skills, and the level of outcomes of the use of digital technology are very popular in contemporary literature and comprehensively depict the digital progress of a country. Ignoring some aspects of the digital divide can present a distorted picture of digital progress (Denissova et al., 2025). This information helps policymakers in developing strategies for mitigating digital inequality.

Measurement approach - measurements of indicators of digital progress through the examination of experts' opinions or by conducting surveys introduce subjectivity in the formation of the index because the ratings are a representation of attitudes and biases of individuals (Sidorov & Senchenko, 2020). By using indicators that are physically measured, objectivity is added to the measurement process. A more reliable source of information is provided by objectively measured indicators. The use of subjective measures can present a disordered picture of digital development if an inadequate population is sampled.

Data source - well-known data sources have strong credibility and accuracy of information, while less prominent sources can be compromised due to lack of transparency in data collection (Oloyede et al., 2023). All official government strategies and action plans rely on formal reports so their accuracy cannot be questioned.

Normalization methodology - the raw collected data that form indexes are frequently expressed in different units of measure. To facilitate a precise comparison, it is necessary to normalize the collected data as proposed by Sidorov and Senchenko (2020). Different normalization techniques lead to diversity as stated by Greco et al. (2019). Therefore, policymakers need to be aware of these differences in results to correctly interpret and utilize them.

Weighting method - enables the allocation of the importance of indicators or dimensions in accordance with the impact on the assessment of digital progress (Sidorov & Senchenko, 2020). Different indicators provide a smaller or larger informative value to the formation of the index, so by giving weights, the influence of less significant indicators on the final score of the index is mitigated and the influence of important indicators is strengthened. This step contributes to balanced index results. For developing formal policies, important areas of digital development must be highlighted to prevent less important features from limiting the index accuracy (Giovanni et al., 2005).

Publication frequency - the time interval for the press release report with the updated index results (Siqueira et al., 2019; Lnenicka et al., 2022). Continuous publication allows policymakers to analyze the dynamics.

Indicator update frequency - the time frame for periodic adjustment of the structure and indicators of the index in line with trends in information society. This indicator points out to an emerging challenge that is the inconsistency of results produced by the same index after its revision (Lnenicka et al., 2022), a topic that is rare mentioned in the literature. By updating the index's structure, policymakers can follow upcoming trends in the area and update action plans and strategies accordingly.

The proposed framework is flexible in several terms. The study uses a three-point interval scale to maintain consistency in evaluating diverse criteria and to overcome potential subjectivity. Broader scales, such as five-point or seven-point scales, can provide detailed data granularity; however, in that case, experts' evaluations must be taken into account to justify derived values. Therefore, the three-point scale introduces simplicity into the decision-making process and allows transparent comparisons. It is based on the assumption of equal conceptual distances. Another important fact is that in this case, all criteria are considered as beneficial meaning that a higher evaluation is desirable. This rule can also be a subject of change depending on the decision-making context and decision-makers preferences. Decision-makers have the flexibility to add or remove any criteria and alternative (index) or to adjust the importance of each attribute that serves as a criterion. For instance, a wide geographical coverage may not always be an important question in selecting an adequate index. Alternatively, a public frequency may be irrelevant in the case when the countries' digital development is evaluated for one year.

The collinearity problem between distinct criteria was avoided due to clear definitions of the concepts they measure. Even if some of the criteria might look related, they contextually measure different aspects. For example, the number of indicators is diverse compared to the multidimensionality of the index because a higher number of indicators does not assure that different dimensions are being measured. In the same way, the regular publishing does not confirm that index structure is being revised to adjust to the specific digitalization trends. As a result, it may not be updated.

3.2. Research methodology

The applied research methodology followed a sequence consisting of the implementation of the MEREC method for calculating objective criteria weights and various MCDMs (CoCoSo, MARCOS, ARAS, CODAS and EDAS) for prioritizing global digital development indexes as alternatives.

The first step in all MCDM methods is to create a decision-making matrix (X) that is described as follows (Keshavarz-Ghorabaee et al., 2021):

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}, i=1,\ldots,m; \quad j=1,\ldots,n, \tag{1}$$

where the element x_{ij} is the value of alternative i according to the j-th criterion. In this study, six alternatives ($m=6$) in the form of indexes (NRI, EGDI, DESI, IDI, IMD and GDI) are evaluated using nine diverse criteria (GC, NI, MI, CDD, MA, DS, NM, PF and IUF) ($n=9$). Decision matrix X reflects the input data into the MCDM methods while ranking lists are the outcome. The criteria can be divided into beneficial and non-beneficial (cost) type of criteria if they add or reduce to the value of prioritization goal. The importance of each criterion is described by an objective weight coefficient w_j where w is the weight value of the j-th criterion. The sum of all criteria weight coefficients is limited to 1 and expressed in equation (2).

$$\sum_{j=1}^{n} w_j = 1 \tag{2}$$

The initial weight coefficients are calculated using the MEREC method. Method inputs are defined as a decision-making matrix described in equation (1) and the outputs are the objective weights of the criteria. Additionally, the Shannon entropy method is implemented as a complementary method for sensitivity testing for weight alterations. This method has already been used in the area of digital development (Brodny & Tutak, 2015).

3.2.1. Objective weighting methods

The Method based on the Removal Effects of Criteria (MEREC) is a multi-criteria approach for objectively determining weighted values of criteria that is selected in this study. The method was developed in 2021 by the authors, Keshavarz-Ghorabaee et al. (2021). The MEREC method varies from other methods for determining criteria weights because it does not rely on the criteria's variability (Ecer & Aycin, 2023). The application is based on the impact that the removal of each criterion individually has on the outcome of the alternatives (Kou et al., 2025). If the deviations of the value of the alternatives are greater upon eliminating a certain criterion, that criterion will assume greater importance (Štilić et al., 2024). Recent literature presents fuzzy form and hybrid MEREC with various multi-criteria methods (Abdelaal et al., 2024; Chaurasiya & Jain, 2024; Štilić et al., 2024; Kou et al., 2025). The basic steps in MEREC are presented as following (1-6):

1. Forming the decision-making matrix. The matrix is described as X expressed by equation (1).
2. Normalizing the decision-making matrix. The normalization is performed linearly, depending on the type of criterion (beneficial/non-beneficial) as shown in equation (3) (Chaurasiya & Jain, 2024).

$$n_{ij}^{x}=\begin{cases} \dfrac{\min x_{ij}}{x_{ij}} & if \quad beneficial \\ \dfrac{x_{ij}}{\max x_{ij}} & if \quad non-beneficial \end{cases} \tag{3}$$

3. Calculating the total value performance. The total value performances (S_i) are calculated for each alternative according to the entire set of criteria with all criteria assigned equal significance as presented in equation (4) (Keshavarz-Ghorabaee et al., 2021).

$$S_i=\ln\left(1+\left(\frac{1}{n}\sum_{j}\left|\ln(n_{ij}^{x})\right|\right)\right) \tag{4}$$

4. Eliminating criteria. The next step follows by removing individual criteria and after each elimination, the outcome of alternatives without that criterion (S'_{ij}) is calculated.

$$S_{ij}^{'} = \ln\left(1 + \left(\frac{1}{n}\sum_{k,k\neq j}\left|\ln(n_{ik}^{x})\right|\right)\right) \tag{5}$$

5. Measuring deviations. Following the criteria elimination procedure, the value of absolute deviation (E_j) is calculated separately for each criterion, indicating the variations in the alternative's outcome. This process is described in the equation (6).

$$E_j = \sum_i \left|S_{ij}^{'} - S_i\right| \tag{6}$$

6. Calculating objective weights. The final objective weight coefficients are given by the equation (7) that expresses the elimination effect.

$$w_j = \frac{E_j}{\sum_k E_k} \tag{7}$$

A greater deviation resulting from the elimination of a criterion corresponds to a higher weight coefficient w_j assigned to the j-th criterion (Keshavarz-Ghorabaee et al., 2021).

Shannon entropy is a method developed by Shannon (1948). Its concept belongs to the information theory and represents a measure of diversity among the information (Ali et al., 2023). It could also be referred to as a measure of uncertainty (Ali et al., 2023). If the distribution among the data is higher so the value of entropy will increase therefore the observed criterion will achieve a lower weight coefficient (Saraiva, 2023).

The elementary steps in implementing the Shannon entropy are given as follows (Shannon, 1948):

1. Forming the decision-making matrix. The matrix is described as matrix X presented by equation (1).

2. Normalizing the decision-making matrix. The formula for calculating the normalized values (p_{ij}) is given as a ratio of element x_{ij} and a sum of the elements that belong to the same criteria.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{8}$$

3. Calculating the entropy.

$$E_j = -k\sum_{i=1}^{m} p_{ij}\ln(p_{ij}) \tag{9}$$

where k is a positive constant derived from a reciprocal natural logarithm of the number of alternatives (m).

$$k = \frac{1}{\ln(m)} \tag{10}$$

4. Calculate the final objective weights. The procedure for determining the objective weights of each criterion is described in equation (11).

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n}(1 - E_j)} \tag{11}$$

3.2.2. Multi-criteria prioritization methods

The Combined Compromise Solution (CoCoSo) is a contemporary multi-criteria method that integrates simple additive weighting (SAW) and exponentially weighted product (EWP) (Dwivedi & Sharma, 2022). It was introduced to the public by Yazdani et al. (2019). The application procedure consists of multiple steps described below (1-5):

1. Forming the decision-making matrix. The matrix is described in matrix X expressed by equation (1).

2. Normalizing the decision-making matrix. The next step is the normalization of the decision-making matrix depending on the type of criteria as in equation (12) (Khan & Haleem, 2021).

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} & if \quad beneficial \\ \dfrac{\max\limits_i x_{ij} - x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}} & if \quad non-beneficial \end{cases} \tag{12}$$

3. Summing the weighted values. The subsequent step involves summing the weighted values of each alternative (S_i) presented by the equation (13) (Yazdani et al., 2019).

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \tag{13}$$

4. Calculating the weighted product. The multiplication of the weighted values' product (P_i) is implemented in equation (14), aligning with the EWP method (Yazdani et al., 2019).

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{14}$$

In the next step, three aggregate values (equations 15-17) are calculated as a combination of previously derived matrices. These values form the elements of the final aggregation according to which the alternatives are ranked (Yazdani et al., 2019).

$$k_{ia} = \frac{P_i + S_i}{\sum\limits_{i=1}^{m} (P_i + S_i)} \tag{15}$$

$$k_{ib} = \frac{S_i}{\min\limits_i S_i} + \frac{P_i}{\min\limits_i P_i} \tag{16}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\left(\lambda \max\limits_i S_i + (1-\lambda) \max\limits_i P_i\right)} \tag{17}$$

where λ is a value between 0 and 1. In this case, the authors use the value of 0.5 that is typically used in such studies (Khan & Haleem, 2021).

5. Calculating the final rank values.

$$k_i = \left(k_{ia} k_{ib} k_{ic}\right)^{1/3} + \frac{1}{3}\left(k_{ia} + k_{ib} + k_{ic}\right) \tag{18}$$

The multiple aggregation of the sum (k_{ia}) and weights (k_{ib}) and then the compromise solution (k_{ic}) mitigates the effects that extreme values can have in the case of the application of only individual aggregation (k_i), which could significantly distort the ranking results (Khan & Haleem, 2021). The advantage of this method is that the ranking is not sensitive to fluctuations in the criteria's value.

Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) represents a novel multi-criteria decision-making method developed by Stević et al. (2020). The method involves determining the ideal (*ai*) and anti-ideal (*aai*) solution according to which the optimal solution or alternative is derived (Stanković et al., 2020; El-Araby, 2023). The calculation consists of the following several steps (1-7):

1. Forming the decision-making matrix. The initial decision-making matrix is described as matrix *X* expressed by equation (1).

2. Finding ideal and anti-ideal alternatives. In the case of beneficial criteria, the ideal is the maximum value and the anti-ideal is the minimum value in the decision-making matrix *X*. For cost criteria, the rule is in the opposite direction.

3. Normalizing the decision-making matrix. This step is carried out by dividing the individual value with the ideal or anti-ideal value in relation to the nature of the criterion as in equation (19) (Stević et al., 2020).

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{x_{ai}} & if \quad beneficial \\ \dfrac{x_{ai}}{x_{ij}} & if \quad non-beneficial \end{cases} \tag{19}$$

4. Weighting the normalized decision-making matrix. Subsequently, the normalized values are multiplied with the weighting coefficients (w_j) that are calculated using another MCDM method, which is employed to calculate the significance of the criteria (Stanković et al., 2020). This is described in the equation (20):

$$v_{ij} = n_{ij} \times w_j \tag{20}$$

5. Calculating the utility coefficients. Afterwards, the utility coefficients for the ideal (K_i^+) and anti-ideal (K_i^-) solutions are determined as in equations (21) and (22). The S_i value is the sum of v_{ij} for each alternative, while S_{ai} are the summed ideal values of the ideal alternative and S_{aai} are the summed anti-ideal values of the anti-ideal alternative.

$$K_i^- = \frac{S_i}{S_{aai}} \tag{21}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{22}$$

6. Calculating the utility functions. The detailed formulas for calculating utility positive $f(K_i^+)$ and negative $f(K_i^-)$ functions are described subsequently in (23) and (24).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{23}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{24}$$

7. Calculating the total utility function. The total utility function serves as the foundation for ranking, where the higher value means a better-ranked alternative (Duc Trung, 2022). This coefficient value $f(K_i)$ integrates the previous two values as demonstrated in equations (23) and (24) (Stević et al., 2020).

$$f(K_i) = \frac{K_i^- + K_i^+}{1 + \dfrac{1 - f(K_i^+)}{f(K_i^+)} + \dfrac{1 - f(K_i^-)}{f(K_i^-)}} \tag{25}$$

The MARCOS is robust when applying different methods for calculating criteria's weight coefficients, such as equal weighting, rank sum weighting, rank order centroid and entropy weighting (Nguyen et al., 2023). Another advantage is its compliance with other MCDMs such as simple additive weighting and preference selection index (Huy et al., 2022). However, the main drawback of this method is its susceptibility to outliers, because the calculations of utility coefficients are based on the minimum and maximum values of the initial decision matrix.

The Additive Ratio Assessment (ARAS) method is classified in the group of multi-criteria decision-making methods and was developed in 2010 by Zavadskas and Turskis (2010). The main advantage of the ARAS method is easy implementation in several steps and a comprehensible model (Zavadskas et al., 2010). The ARAS procedure includes the following steps (1-6):

1. Forming the decision-making matrix. The original decision-making matrix is expressed as matrix *X* in equation (1).

2. Finding the optimal value. If the criteria are beneficial the optimal value (x_{0j}) is the maximum value of the criteria, in opposite if the criteria are non-beneficial the optimal value (x_{ij}^*) is the minimum value of the criteria. Therefore, a hypothetical alternative with ideal values is formed as a base for comparison (Zavadskas & Turskis, 2010).

3. Normalizing the original decision matrix. The normalization of the decision matrix is presented by formula (26) that varies on the type of criteria.

$$\bar{x}_{ij} = \begin{cases} \dfrac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad if \quad beneficial \\ x_{ij} = \dfrac{1}{x_{ij}^{*}}; \bar{x}_{ij} = \dfrac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad if \quad non-beneficial \end{cases} \tag{26}$$

4. Weighting the normalized decision-making matrix. The normalized values of the decision matrix are weighted ($\hat{x}_{ij}$) by the equation (27).

$$\hat{x}_{ij} = \bar{x}_{ij} \times w_j \tag{27}$$

5. Calculating the optimality function. The aggregate weighted values of each alternative represent the optimality function (S_i) described in formula (28) (Turskis & Zavadskas, 2010). The same procedure is applied to find the optimal alternative (S_0).

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}, i = \bar{0}, ..., \bar{m} \tag{28}$$

6. Calculating the utility degree. By comparing the value of the optimality function (S_i) with the value of the optimal alternative (S_0), a ranking is made (Zavadskas & Turskis, 2010).

$$K_i = \frac{S_i}{S_0}, i = \bar{0}, ..., \bar{m} \tag{29}$$

The higher value of the utility degree means a better position in the ranking list.

The main disadvantage of this method is the possible existence of extreme values within one of the alternatives that can distort the ranking values.

The Combinative Distance-based Assessment (CODAS) is a modern multi-criteria decision-making method proposed by Ghorabaee et al. (2016). The core component of the CODAS method is the ranking of alternatives according to the distance measurement of individual alternatives in relation to the worst-case scenario (Kumari & Acherjee, 2022). The first step is identical to most MCDM methods and it includes forming a decision-making matrix. The basic steps in CODAS are described as follows (1-7):

1. Forming the decision-making matrix. The preliminary decision-making matrix is expressed as matrix *X* in equation (1).

2. Normalizing the original decision matrix. The formula is presented in equation (30) and differs for beneficial and non-beneficial criteria (Ghorabaee et al., 2016):

$$n_{ij} = \begin{cases} \dfrac{x_{ij}}{\max_i x_{ij}} \quad if \quad beneficial \\ \dfrac{\min_i x_{ij}}{x_{ij}} \quad if \quad non-beneficial \end{cases} \tag{30}$$

3. Weighting the normalized decision-making matrix. The formula for the weighting step is described in equation (31).

$$r_{ij} = w_j \times n_{ij} \tag{31}$$

4. Defining the negative-ideal solution. The negative-ideal value (n_{sj}) is equal to the minimum weighted value (r_{ij}) of alternative *i* to the *j*-th criterion from step 3.

5. Calculating distances from the negative-ideal solution. The distance measurement is performed using the Euclidean distance (E_i) and the taxicab distance (T_i), which contributes to the consistency of the rankings (Tüysüz & Kahraman, 2020). The derived weighted values are used to calculate the distance of each

alternative from the negative ideal solution defined in step 4 (Ghorabaee et al., 2016). The calculations in equations (32) and (33) are done on weighted values r_{ij} and negative-ideal value n_{sj}.

$$E_i = \sqrt{\sum_{j=1}^{m} (r_{ij} - ns_j)^2} \tag{32}$$

$$T_i = \sum_{j=1}^{m} \left| r_{ij} - ns_j \right| \tag{33}$$

6. Calculating the relative assessment score. By aggregating the two distance measures, we obtain the relative assessment scores (Ghorabaee et al., 2016). The formula for obtaining the value is presented in equation (34).

$$h_{ik} = (E_i - E_k) + (\Psi(E_i - E_k) \times (T_i - T_k)), k = 1, \ldots, n \tag{34}$$

where Ψ is determined by a threshold value of τ that is in this case expressed as 0.02 (Kumari & Acherjee, 2022). The distance between the alternatives is measured by the Euclidean distance (E_i) and the taxicab distance (T_i) if it satisfies the following rule:

$$\Psi(x) = \begin{cases} 1 & if \quad |x| \geq \tau \\ 0 & if \quad |x| < \tau \end{cases} \tag{35}$$

7. Calculating the assessment score. By summing the relative assessment scores, the final scores are obtained, according to which the alternatives are ranked.

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{36}$$

The alternative with a higher assessment score (H_i) attains a more favorable position in the ranking list since its distance from the negative ideal solution is the largest (Kumari & Acherjee, 2022).

Evaluation based on Distance from Average Solution (EDAS) is a multi-criteria method for ranking alternatives presented by Keshavarz Ghorabaee et al. (2015). The essence of the methodology consists in quantifying the distance of the alternatives from the mean (Alinezhad & Khalili, 2019). In this way, the EDAS method demonstrates the relative superiority or inferiority of an alternative compared to the average solution. The initial steps in the application of the method involve the formation of the decision matrix and the calculation of the average values of the criteria. The required steps in EDAS are presented as follows (1-8):

1. Forming the decision-making matrix. The starting decision-making matrix is presented as matrix *X* in equation (1).

2. Calculating the average values. The equation (37) for the arithmetic mean is used to calculate the average values (AV_j) that serve as a reference value for comparison (Torkayesh et al., 2023).

$$AV_j = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{37}$$

3. Calculating the positive and negative distance from the average. The next step involves measuring the positive (PDA_{ij}) and negative (NDA_{ij}) distance of the alternatives in relation to the average solution (Keshavarz Ghorabaee et al., 2015). In this step, the nature of the criteria (benefit/cost) is taken into account. Therefore, equations (38) and (39) are used in case of beneficial criteria, while equations (40) and (41) are used for non-beneficial criteria.

$$PDA_{ij} = \frac{\max(0, x_{ij} - AV_j)}{AV_j} \tag{38}$$

$$NDA_{ij} = \frac{\max(0, AV_j - x_{ij})}{AV_j} \tag{39}$$

$$PDA_{ij} = \frac{\max(0, AV_j - x_{ij})}{AV_j} \tag{40}$$

$$NDA_{ij} = \frac{\max(0, x_{ij} - AV_j)}{AV_j} \tag{41}$$

4. Weighting the normalized decision-making matrix. In the next step, the weighting procedure is performed and the weighted positive (SP_i) and weighted negative (SN_i) distances of the alternatives are calculated (Keshavarz Ghorabaee et al., 2015).

$$SP_i = \sum_{j=1}^{n} w_j \times PDA_{ij} \tag{42}$$

$$SN_i = \sum_{j=1}^{n} w_j \times NDA_{ij} \tag{43}$$

5. Normalizing the weighted positive and negative distances. The procedure is done using equations (44) and (45).

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \tag{44}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)} \tag{45}$$

6. By aggregating normalized positive (NSP_i) and normalized negative (NSN_i) distances in equation (46), the values of the alternatives are derived, according to which the ranking is made (Keshavarz Ghorabaee et al., 2015).

$$AS_i = \frac{1}{2}(NSP_i - NSN_i) \tag{46}$$

A higher value of the alternative (AS_i) brings a better position in the ranking list (Torkayesh et al., 2023). The advantage of the EDAS method is that it mitigates the effects of extreme values on the ranking process by taking average values into account (Alinezhad & Khalili, 2019). Hybrid EDAS models integrated with the regression approach have proven to be effective in scenarios where the number of alternatives changes and an urgent decision need to be made, since this approach shortens the process of assigning ranks (Trung et al., 2023).

4. Research results

Table 3 presents the quantitative assessment of each index according to the given criteria. The EDS criterion, which refers to the economic diversity of the countries included in the indexes, yields no discriminatory power across all alternatives, so it was eliminated from the decision-making process. It means that all Indexes are considering both developed and developing countries. Similarly, the WM criterion, which determines the method of calculating the weight of the components inside the index structure, was omitted from the study. All observed indices were assigned equal weights to groups of criteria thereby falling into the category of subjective weighting approaches. The theoretical explanation for implementing this type of weighting method is not transparent in the reports. Among the remaining criteria, the greatest diversity in ratings appeared in terms of the geographical coverage of the countries (GC) included in the index and the representation of the digital divide (CDD) within the index's indicator framework. NRI, EGDI and DESI cover the physical access to the digital technologies (first level), skills to use them (second level) and benefits that are acquired by individuals or groups from them (third level) within their indicators. The IDI index covers only the physical access to digital technologies (first level), while IMD and GDI cover physical access and skills to use digital technologies (first and second levels). The remaining criteria express the theoretical and practical scope of the indexes.

Criterion	Label	Alternative					
		NRI	EGDI	DESI	IDI	IMD	GDI
Geographic coverage	GC	3	3	1	3	2	2
Economic diversity of the sample	EDS	3	3	3	3	3	3
Number of indicators	NI	3	3	3	1	3	3
Multidimensionality of the index	MI	3	3	3	1	3	3
Coverage of the digital divide	CDD	3	3	3	1	2	2
Measurement approach	MA	2	2	2	3	2	3
Data source	DS	2	2	2	3	2	3
Normalization methodology	NM	3	3	3	3	1	1
Weighting method	WM	2	2	2	2	2	2
Publication frequency	PF	3	2	2	3	3	3
Indicator update frequency	IUF	3	3	3	3	3	1

Table 3. Evaluation matrix with a quantitative rating scale.

4.1. Comparative analysis of the MEREC-MCDM models

By applying the objective approach of eliminating criteria the calculation of weight values was carried out using the MEREC method. The proposed methodology is sensitive to outliers however using the scale 1-3 this problem is minimized. All criteria are marked as beneficial because higher values enhance a higher index rating and their significance is reported in Table 4. The greatest impact on the subsequent ranking of the index are structural modifications. Following the digitalization trends ensures the timely availability of high-quality information, which is crucial for the decision-making process. Then follow the quantity of indicators within the structure of the index and the scope of the measurement area. More comprehensive indexes with a larger number of indicators are effective for ranking. The important dimensions were previously confirmed by Oloyede et al. (2023) and Denissova et al. (2025).

Criterion / Alternative	GC	NI	MI	CDD	MA	DS	NM	PF	IUF
Type of criteria	max	max	max	max	max	max	max	max	max
MEREC weight coefficient (w_j)	0.140	0.164	0.164	0.138	0.026	0.026	0.130	0.049	0.165

Table 4. Objective weight coefficients using MEREC method.

Index ranking was conducted under the scope of five MCDM methods to test the validity and reliability of the results. The ranking results are presented in Table 5.

Method	CoCoSo		MARCOS		ARAS		CODAS		EDAS	
Index	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
NRI	1.955	1	0.895	1	0.982	1	0.260	1	0.987	1
EGDI	1.742	2	0.880	2	0.967	2	0.258	2	0.949	2
DESI	1.452	6	0.795	3	0.868	3	-0.303	6	0.699	3
IDI	1.479	5	0.628	6	0.695	6	0.066	3	0.322	5
IMD	1.544	4	0.732	4	0.792	4	-0.104	4	0.469	4
GDI	1.616	3	0.647	5	0.706	5	-0.175	5	0.284	6

Table 5. Final ranking scores using different MEREC-MCDM techniques.

The applied MCDM methods validate the NRI index as the first-ranked and the most favorable for the assessment of digital development, while the EGDI index is positioned second in terms of structural adequacy. The findings indicate the consistency of the decision-making process without deviations in the ranks. The difference in the scores of these two indices is negligible compared to the other lower-ranked indices, suggesting minor differences in terms of the quality and information they provide. The NRI index achieves a limited territorial scope (133 countries), with an annual release frequency. With these advantages, NRI provides an opportunity for comparative analysis and continuous monitoring of changes. The structure of the NRI index is routinely updated to modernize and refine the index according to the dynamics of the digital landscape. In contrast, EGDI covers a broader number of countries (193 countries) but is published biennially, which leaves the possibility that short-term fluctuations in digital flows go unnoticed. Both indexes, NRI and EGDI, in their structure contain a large number of indicators that can be connected to the analysis of the digital divide at all three levels, offering a comprehensive instrument for measuring digital development. The reports transparently present the data normalization methodology and cite credible sources of information. These two indices are rated as the most relevant in decision-making.

Additional confirmation of the stability of the MCDM ranking results is the consistency of the ranking of the IMD index, which took the fourth position across all MCDM methods. IMD can be classified as a medium-index with structural adequacy. The average territorial coverage of 67 countries provides a limited picture of digital development. IMD contains a large number of indicators, but according to it, the third level of the digital division, which refers to the measurement of the effects of the use of digital technology is lacking. The index fails to provide an explanation of the method for data normalization and information on whether the normalization procedure was implemented.

The remaining three indices DESI, IDI and GDI are characterized by fluctuations in the rank from the third to the sixth position, reflecting their sensitivity to the choice of ranking method. Although it has a larger number of indicators, adequate data sources and a robust framework, DESI is constrained in its geographical scope because it focuses on EU countries. This causes inferior ranking according to the CoCoSo and CODAS methods. In addition, the DESI report is published every second year, which affects the lack of a regular annual review of the digital development status. IDI and GDI have a smaller number of indicators in their structure, and according to them, the digital divide cannot be analyzed in terms of possession, use and benefit from digital technology, unlike DESI. According to the given weighting values of the criteria, the number of indicators and the coverage of the digital divide are crucial in the process of evaluating alternatives, which illustrate both criteria by which the IDI is rated weaker. The report on the GDI index lacks information on data normalization and does not provide any guidance on how to update the structure. It is a recently established index, which reduces its reliability and credibility. The difference in the ranking of the IDI and GDI indices arises only from the frequency of structural updates because the GDI has not been subject to changes until now.

In order to perform a more complex comparison of alternatives according to considered MCDM methods, the voting method was applied. The results of the overall ranking were calculated using a methodology according to which the ranks represent ratings and the index with the lowest summed value of the votes is ranked first, followed by the others in ascending order. The results are reported in Table 6.

Criterion	Alternative					
	NRI	**EGDI**	**DESI**	**IDI**	**IMD**	**GDI**
Voting score	5	10	21	25	20	24
Rank	1	2	4	6	3	5

Table 6. Aggregated ranking using voting approach.

A comparative analysis of differences and similarities in the application of MCDM methods is shown in Table 7. Author Dua (2024) suggests the use of Spearman's correlation rank for analyzing relationship among various MCDM ranking scores. Absolute concordance in ranks is present in the pair of MARCOS and ARAS. Despite differing normalization techniques (the MARCOS method performs normalization in relation to the ideal and anti-ideal solution while the ARAS method performs normalization according to the share of the alternative in relation to the sum of the scores of all alternatives), the obtained values have a similar proportionality that affects the allocation of the same ranks. The MARCOS and ARAS methods show a partial concordance in the ranks with the EDAS method evidenced by a Spearman correlation coefficient of 0.94. The EDAS method is similar to the MARCOS method in the normalization of data according to positive and negative deviations from the average value, while MARCOS considers ideal and anti-ideal values. Conversely, the ARAS methodology relies on the average values of the alternatives according to the given criteria however the final ranking is performed comparing the alternative values with the ideal hypothetical alternative values. These three measures are related as they offer insight into the divergence of index values from ideal values.

The second category of CoCoSo and CODAS methods analyzes the distance and difference between indices. Spearman's correlation coefficient of ranks according to these methods is 0.77. Both methods share a comparable principle on the data normalization but a different procedure for ranking the alternatives. These differences can be evidenced by the high value of the average absolute difference in ranks between them, which equals 0.67.

MARCOS, ARAS and EDAS methods were chosen to rank the structural adequacy of the index based on a reference point that can be the average, ideal or anti-ideal value of the index rating according to the given criteria. Therefore, these methods yield more consistent findings. In contrast, CoCoSo and CODAS are more sensitive to extreme values due to deviation in values between alternatives but provide more accurate proof of the difference between similar alternatives.

Method I	**Method II**	**Average absolute difference in ranks**	**Spearman's correlation rank**
CoCoSo	MARCOS	1.00	0.60
CoCoSo	ARAS	1.00	0.60
CoCoSo	CODAS	0.67	0.77
CoCoSo	EDAS	1.00	0.49
MARCOS	ARAS	0.00	1.00
MARCOS	CODAS	1.00	0.49
MARCOS	EDAS	0.33	0.94
ARAS	CODAS	1.00	0.49
ARAS	EDAS	0.33	0.94
CODAS	EDAS	1.00	0.60

Table 7. Pairwise similarity and difference matrix.

4.2. Effect of diverse weighting method

There is a partial convergence in the values when comparing the Shannon Entropy weight coefficients with the previously calculated values by the MEREC method (Table 8). This variance mostly derives from the weights of territorial coverage (MEREC: 0.140, Entropy: 0.139), coverage of the digital divide (MEREC: 0.138, Entropy: 0.139) and publication report frequency (MEREC: 0.049, Entropy: 0.040). The entropy approach prefers indices with the officially published normalization methodology ($w_{NM}=0.229$). The positive value of the correlation coefficient of 0.707 demonstrates the high degree of methods compatibility.

Criterion / **Alternative**	**GC**	**NI**	**MI**	**CDD**	**MA**	**DS**	**NM**	**PF**	**IUF**
Type of criteria	max	max	max	max	max	max	max	max	max
Shannon Entropy weight coefficient (w_j)	0.139	0.119	0.119	0.139	0.048	0.048	0.229	0.040	0.119

Table 8. Objective weight coefficients using Shannon Entropy method.

The weight coefficients from Table 8 were used to test the rank stability with MCDM methods. The results are demonstrated in Figure 2.

A noticeable evidence from the graphic illustration proves the stability of the NRI and EGDI indices. Their consistency remains regardless of the chosen weight calculation method and ranking method. These two indices receive high marks that do not vary in relation to the criteria. In addition, the DESI index, as a relatively weaker rating, provides stability in the ranks when considering different methods for calculating the weighted importance of the criteria. An obvious fluctuation in ranks is present in the IDI and IMD indices, which are evaluated with different grades ranging from 1 to 3. The evidence demonstrates that the entropy method in its hybrid form with CoCoSo, MARCOS, ARAS and EDAS is sensitive to index performance grades. These models are particularly useful when it is necessary to emphasize the difference between alternatives. The uniformity of ranks when altering the method for calculating weighting coefficients is validated by the coefficients of Spearman's rank correlation analysis (CoCoSo: $\rho = 0.829$, MARCOS: $\rho = 0.829$, ARAS: $\rho = 0.829$, CODAS: $\rho = 1.000$, EDAS: $\rho = 0.943$).

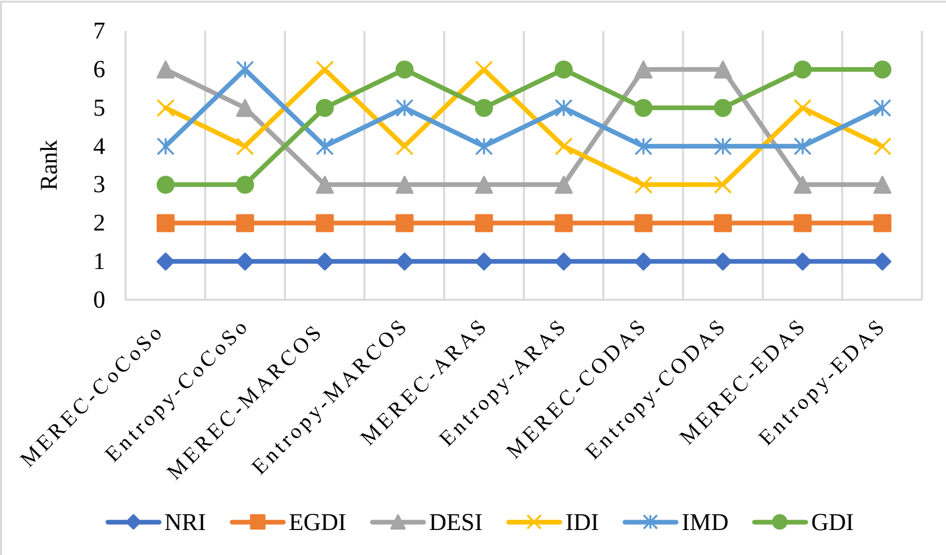

Figure 2. Stability of MCDM ranks in relation to changing the method for determining the weights to Shannon Entropy.

5. Discussion

This paper analyzes eight internationally recognized indexes for measuring digital development (NRI, EGDI, DESI, DGI, DAI, IDI, IMD and GDI) to determine which aligns more closely with the applied evaluation framework. Initial analyses removed the DAI and DGI indexes from comparison due to the lack of reports for the reference year 2024.

An integrated evaluation framework was developed using eleven different criteria for assessing six alternatives. With the hybrid approach of MEREC and other MCDM methods, namely CoCoSo, MARCOS, ARAS, CODAS and EDAS, five MCDM models were formed for the purpose of prioritization. The decision on methods was made to ensure that each provided a different normalization process and diversity of methods to find optimal solution. Ranking based on the MARCOS and ARAS methods indicated a complete positional overlap. The stability of the model is confirmed by the ranking results for the first (NRI), second (EGDI) and fourth (IMD) positions that have the same alternatives across all MCDM models. NRI and EGDI were characterized by strong and consistent ratings according to the highest importance attributes while IMD showed variability in score. The remaining alternatives (DESI, IDI, GDI) have recorded multiple deviations from the average values. The results remain stable even in the case when a different weighting method is applied (Shannon Entropy).

A comparative analysis of methodological similarities and differences conducted by the absolute difference between ranks and the Spearman correlation rank confirmed that reference-based methods (MARCOS, ARAS, EDAS) yield more consistent results than distance-based methods (CoCoSo, CODAS). The latter were found to be more sensitive to outliers, making them preferable when the decision-making process involves identifying exact differences between alternatives.

The proposed theoretical framework identified three attributes such as update frequency, the quantity of indicators and multidimensionality of the index as essential in the decision-making process. The combination of these three attributes captures both the theoretical and practical scope of digitalization within a dynamic environment. Overly narrow indicator structures that include one or two aspects of digital progress risk excluding important domains of development. In reverse, an overly broad multidimensional structure can reduce the impact of key features due to the information overload. The most suitable are indices that depict the digital progress via a balanced set of dimensions and a structure that is periodically revised to align with social and economic priorities.

NRI as a leading index achieves high performance in the regularity of updating the index structure ($w_{IUF}=0.165$) since control and changes are performed periodically. Frequent modifications contribute to the inconsistency of ranks and create a rather large gap in comparative analyses of historical data. The NRI report for 2024 has undergone minor changes compared to the previous 2023 report. Indicators such as tertiary enrollment, gross domestic expenditure on research and development by the business sector, high-tech manufacturing and exports have been removed (NRI report, 2023). However, more innovative metrics such as the number of venture capital deals invested in AI and public cloud computing market scale were introduced instead (Portulans Institute, 2023). In 2017 the publication of IDI index was paused due to problems with available data. A new report issued in 2023 provided an entirely new concept, so a comparative analysis was limited (International Telecommunication Union, 2025). This problem was also addressed by Lnenicka et al. (2022) showing that it is rarely discussed in contemporary literature. An additional problem emerges from the reverse scenario due to the lack of revision, because trends in the field of information technologies cannot be captured if we constantly measure the same indicators.

In the case of digital progress, an additional subject for further development is monitoring the digital divide. If the index lacks a structure for assessing digital inequality in terms of access, use and social and economic benefits from technology, then it is incomplete. A simple assessment of the use of digital technology fails to provide information on whether the application of these technologies has facilitated or hindered an activity. NRI is characterized by a large number of individual indicators ($w_{NI}=0.164$). It also includes a large number of dimensions ($w_{MI}=0.164$) through the integration of information technologies across fields of society, the business sector and public administration. The index deals with questions of digital trust and inclusion as important ethical and privacy terms in future development. Unlike the NRI index, the IDI index focuses on the accessibility and scale of these technologies but does not analyze their impact on other critical domains. Consequently, the IDI index is rated as less comprehensive because its structure is formed on the basis of a minimal 11 indicators. The obtained results according to the number of indicators align with the recommendations of the European Union & Joint Research Center (2008), who indicate that effective indexes are neither too simplistic nor overly complex. The IDI index is regarded as narrowly specialized aimed at measuring the share of information technology users while ignoring trends such as the side effects on the economy and society. In this sense, the IDI index does not deal with the digital divide ($w_{CDD}=0.138$) because there is no data on the consequences of technological use, the development of e-government or digital inclusion. The GDI and IMD are presumed to effectively measure the development of digitalization at the macro level, but these indices also omit measurements that include issues of unequal territorial or gender access to technology for individuals. A classical example of an index that measures the digital divide adopted in this paper is the DESI index. This index relies on indicators of access and use of information technologies (e.g., mobile and fixed broadband coverage), measures skills for use (internet user skills and advanced skills and development) as well as the use of information technologies at the individual level (e-Government users). Similarly to DESI, the NRI index addresses the issue of equal use of information technologies by devoting the third sub-pillar, namely inclusion, to the main governance pillar. The findings were confirmed in the study by Denissova et al. (2025), who point out the need to include all three levels of the digital divide to form a realistic index. In terms of the technical aspect, IMD and GDI ignore valuable information about whether normalization ($w_{NM}=0.130$) was carried out on the raw data, thereby reducing their significance. Authors Sidorov and Senchenko (2020) confirm that the absence of normalization questions the precision of the obtained results. NRI and EGDI index provide complete insight into the core methodology, which makes these indices transparent and desirable for professional use. The IMD and GDI indices, in addition to the DESI index, analyze a limited number of countries ($w_{GC}=0.140$). This limitation prevents a global or regional analysis of digital development. For example, the DESI index has EU countries in its focus, while the IMD and GDI, although they have a global focus, omit technology hubs in Asia such as Israel and Hong Kong. Such situations can affect the analysis of regional differences and omit the influence of large technological players on the global market, as proved by Oloyede et al. (2023).

6. Conclusion

The proposed framework for selecting the most appropriate index aims to support decision-makers such as managers and policymakers by guiding them in choosing a transparent, consistent and comprehensive measurement instrument. The paper's additional value is reflected in the topic preference, as academic scholars have not previously addressed this issue using the proposed methodological and theoretical framework. This analysis highlights an important observation that not every global index tackles emerging challenges. Comparative analysis raises the awareness of social differences such as access to and benefits derived from the new technology. This allows government officials to formulate investment policies adjusted to the active inclusion of digitally marginalized populations in ongoing digitalization processes. Another important topic that many indices ignore is digital trust and privacy, which are essential for further digital development. Transparency in the data collection and ranking is equally important. Practical recommendations include using an index that offers broad geographical coverage with frequent updates to mitigate bias and track trends. During the ranking process, not all indicators are of equal importance. Therefore, it is desirable to include objectively calculated weights in the index structure. For example, in this study, the frequency of index updates plays a more significant role in its selection than the data collection method itself. If the index is not adapted to the environment, data can be collected both subjectively and objectively but will not reflect the real picture of digital progress. Its structure lacks important indicators for that development phase and will not provide information on emerging trends. Such guidelines contribute to improving public trust in strategic planning and strengthening the initiative for digital progress in the long term.

The theoretical contribution is reflected in the newly developed hybrid model based on multi-criteria methods that allows for the assessment of the digitalization index as an analytical tool. Deciding on an appropriate index is based on criteria with varying importance, as not all criteria provide equally important information. This approach offers a theoretically supported framework as an alternative to the traditional arbitrary choice of indices and provides further insight into the issues of measuring digital development.

The main drawback of the study is reflected in the small alternative dataset. The focus of the study was on well-known and recognized global indices that are common sources of data and information for decision-makers. Therefore, the indices that were developed as part of the academic research projects and scholarly research were intentionally left out. This limitation leads to the question of relying on public documents as the primary source of information. The reliability and transparency of the dataset cannot be subjected to verification. The authors recognize another limitation in the form of using an ordinal scale for assessing indexes. The 1-3 ordinal scale was used to introduce simplicity into the multi-criteria analysis for qualitative criteria. However, some of these criteria could be quantified using alternative scales. Further research could include debate on this topic.

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