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Review

Human development and data envelopment analysis: A structured literature review ☆, ☆☆

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ABSTRACT

Given the importance the concept of productive efficiency has on analyzing the human development process, which is complex and multidimensional, this study conducts a literature review on the research works that have used the data envelopment analysis (DEA) to measure and analyze the development process. Therefore, we researched the databases of Scopus and Web of Science, and considered the following analysis dimensions: bibliometrics, scope, DEA models and extensions used, interfaces with other techniques, units analyzed and depth of analysis. In addition to a brief summary, the main gaps in each analysis dimension were assessed, which may serve to guide future researches.

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1. Introduction

The particularities of the development processes, both economic and human, have been increasingly studied, albeit these processes, especially the latter, are still not fully understood. It should be emphasized that human development includes

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expanding well-being for all people and increasing the possibilities of individual choice [91], and it can be defined as the process of expanding people's capacity to perform freely chosen core value activities [82]. In broad terms, the human development approach appeared as a means to reallocate human beings at the center of actions related to politics, economy and society, in such a way that the central concern is no longer how much is being produced, but rather how this affects people's quality of life [41].

Bearing in mind how new the idea of human development is, and how difficult it is to measure and analyze it, given its multidimensional nature, the data envelopment analysis (DEA) can greatly contribute to this process, by making it possible to better study and understand it. DEA is an operational research method developed by Charnes et al. [16], which through the empirical construction of a frontier, allows calculating the efficiency of a set of units, designated as decision making units (DMUs). The main attributes of DEA are its versatility and its capacity to be adapted to many different situations.

According to Liu et al. [57], the number of accumulated papers about DEA applications has exceeded the number of purely methodological ones since 1999. The survey of DEA applications conducted by these authors, however, was focused only on industrial applications and the gap in the systematization of the studies that used DEA to evaluate human development continues to exist. This gap will be filled with this work.

In line with this view, the objective of this research paper is to identify and systematize information regarding studies that have used DEA to evaluate the human development process, while pointing out possible directions for future research. To this end, a literature survey using a structured literature research was conducted because, according to Jabbour [49], it enables to:

1. Integrate the results of the articles assessed and relate them to the emerging issues on the topic researched.
2. Analyze in depth the most important studies that incorporate state-of-the-art research on a theme.
3. Identify possible gaps and challenges for future research.

Taking this into account, the outline of this paper is as follows: the major DEA models and extensions are described in Section 2; the research method is presented in Section 3; the results are discussed in Section 4; finally, in Section 5 some conclusions are presented about this work.

2. Data envelopment analysis

DEA is a mathematical procedure based on linear programming, which can determine the set of weights that maximizes the efficiency of a DMU, allowing it to incorporate multiple inputs and outputs into a single value, without the need to convert them into a common unit of measure [22]. Under this basic principle, a big number of models and extensions were developed; part of these was used in the research about human development and they will be addressed in the next two subsections. More details about these and others models and extensions of DEA can be found in Cook and Seiford [20]; a survey about the most cited journals and researches in DEA literature can be found in Liu et al. [56].

2.1. Models

DEA can be expressed as a series of models, whereas the type of returns to scale is what characterizes the two main ones: (a) CRS (constant returns to scale), or CCR which is an acronym for Charnes, Cooper, and Rhodes [16]; and (b) VRS (variable returns to scale) or BCC which is an acronym for Banker, Charnes, and Cooper [4]. Simply put, while the CCR model assumes that outputs always grow proportionally to inputs, in the BCC model this proportionality is not required, as a DMU may display returns to scale: (a) *increasing*: where outputs grow proportionally more than inputs; (b) *constant*: where there is proportionality; or (c) *decreasing*: where outputs grow proportionately less than inputs.

The CCR and BCC models are classified as radial models. This occurs because the efficiency index of a DMU will represent either the equiproportional reduction of all inputs or the equiproportional increase of all outputs needed to make this DMU more efficient. Radial models therefore require first selecting an orientation, which can be ‘input orientation’ or ‘output orientation’. Other types of radial models are the DRS (decrease returns to scale), working with decreasing and constant returns to scale; and IRS (increase returns to scale), working with increasing and constant returns to scale.

Besides these, there are the non-radial models, whose efficiency is based on the slack concept, which represents how much each input and each output, respectively, should be reduced or increased until the DMU reaches the frontier. These models, unlike the radial ones, do not rely on equiproportional increases or reductions of inputs or outputs, and can simultaneously work in both directions. The additive model of Charnes et al. [18] was the first model to be developed, which can work with both constant returns as well as with variable returns to scale. An advancement of this model was the Slack Based Measure (SBM), proposed by Tone [89], which has the advantage of generating an index between zero and one as a result. Another commonly used non-radial model is the Russell Measure (*RM*), which was developed by Pastor et al. [74].

Finally, the multiplicative models, which were innovatively presented in Charnes et al. [17] must be mentioned. Unlike the aforementioned models, these models do not originate from a linear combination of inputs and outputs, but rather from a geometric combination between variables.

2.2. Extensions

For each of the models presented in the previous subsection, some extensions were developed with several objectives, some of which are (a) breaking the tie between efficient DMUs; (b) incorporating experts' opinions; (c) approaches to deal with panel data; (d) approaches to determining common weights etc. Table 1 shows a brief summary of all DEA extensions that have been used in studies on human development, grouped according to the role they play.

3. Method

The structured literature review followed the method proposed by Lage Junior and Godinho Filho [52], which was later disseminated by Jabbour [49]. This method is summarized in the following steps:

- *Step* 1: Assessing the articles published in major databases, using a set of pre-established keywords.
- *Step* 2: Screening the articles found by reading their abstracts.
- *Step* 3: Developing a classification and an analysis system that can represent all dimensions of the object researched.

Table 1
DEA extensions that have been used in studies about human development.

Function	Extension	Description	Developed by
Tiebreaker	Cross-evaluation (CE)	Consists of taking all the weights obtained by the DEA, and using them to calculate the efficiency of all DMUs	Sexton et al. [83] and Doyle and Green [32]
	Super-efficiency (SupE)	Consists of eliminating from the linear programming model the restriction that limits to one the efficiency of the unit being analyzed	Andersen and Petersen [2]
	Inverted frontier/composite index (IF)	Consists of exchanging the place of inputs and outputs and in the subsequent calculation of the arithmetic mean between the efficiency of the standard and inverted frontiers	Yamada et al. [96] and Leta et al.[55]
	Triple Index (TI)	Consists of the geometric mean of the standard, multiplicative-cross and inverted indexes	Mariano and Rebelatto [63]
Incorporating expert opinion	Direct restriction (DR)	Directly restricts the weight assigned by the DEA	Dyson and Thanassoulis [33]
	Assurance region (AR)	Restricts the weight ratio of two variables	Thompson et al. [87]
	Restrictions on the relative contribution of a variable (RC)	Restricts the rate at which a variable can contribute to the virtual input or output constituted	Wong and Beasley [94]
	Value efficiency analysis (VEA)	The DEA is used to evaluate the efficiency in relation to a Most Preferred Solution - MPS	Halme et al. [44]
Temporal analysis	Malmquist Index (MI)	Index-number that measures the change in productivity over time; it can be decomposed into changes due to technology and due to the efficiency	Caves et al. [13] based in Malmquist [61]
	Window analysis (WA)	Consists in separating the data of a panel in different time slots (windows) and then applying the DEA	Charnes et al. [15]
Others	Sensitivity analysis (SA)	Consists of the test of sensitivity of efficiency to a change in the conditions, such as the removal of a variable	Charnes et al. [18]
	Returns to scale (RS)	Consists of a set of procedures to determine if the relationship between inputs and outputs is proportional (constant returns), more than proportional (increasing returns) or less than proportional (diminishing returns)	Banker [3]
	Common weights (CW)	Methodology to find the common set of weights that optimizes the average efficiency (or other criteria) of DMUs	Despotis [28]
	Non-discretionary variable (NDV)	They are fixed variables, which cannot be increased or decreased to reach the frontier	Banker and Morey [5]
	Clustering (Clust)	Consists of grouping the DMUs with successive applications of the DEA, whereas the efficient units are phased out	Barr et al. [6]

Table 2
Keywords used in this research.

	And	
	Data envelopment analysis	Human development
		Social development
Or		Social indicators
		Welfare
	DEA	Quality of life
		Social performance

Table 3
Number of papers selected from Scopus and Web of Science.

Analysis criteria	Scopus	Web of Science
Papers identified with the keywords	237	109
Work used after consulting the abstract (%)	54 (22.78)	34 (31.19)
Total papers analyzed	**57**	

- *Step* 4: Building the profile of scientific production and key outcomes identified in each article, based on the previously developed classification system.
- *Step* 5: Analyzing the gaps as well as the opportunities and challenges that may guide future research on the topic.

As indicated in Step 1, the database had to be selected and the set of keywords specified so that one might assess the articles. As for the database, the two most important ones, which were also considered in this work, were the Web of Science and Scopus, whereas the second is broader than the first one. As for the keywords, Table 2 shows the set chosen, along with the different combinations tested between them.

As the search was conducted in November 2014, other works may have been published since then.

4. Results

From the consultation performed in the databases with the keywords listed in Table 2 (Step 1), 237 articles were found in Scopus and 109 in the Web of Science, whereas most of them were shared by both databases. After they were screened (Step 2), 54 papers were selected from Scopus, to which three more were added. Such added papers were found by means of an unstructured search that went through the citations contained in the studies assessed. As for the papers in the Web of Science, 34 of the 109 found were selected, all of which were already included in the 54 articles found in Scopus. Table 3 systematizes these results.

After reading all the papers, a system was developed to classify them (Step 3), enabling a broad understanding of their main aspects. This system was developed considering five dimensions, namely:

- Bibliometrics.
- Scope of the analysis.
- DEA approach, which includes the model and DEA extensions, as well as interfaces with other techniques.
- Units analyzed, which includes the quantity and the universe of the DMUs evaluated.
- Depth of analysis, which includes the social term used, the number of variables used and the social dimensions that were taken into account.

Table 4
Analysis of the 57 papers selected.

Research	Evaluated DMUs			Variables		Analysis scope	DEA Approach		
	Type	Geography or economic region	Quantity	Number of inputs	Number of outputs		Model	Extension	Interfaces
Adler et al. [1]	DC	Global	61	4	10	SE and RSE	BCC – O	RC	PCA
Bollou et al. [9]	C	Africa	5	4	3	RSE	CCR – I and BCC – O	No	No
Bernini et al. [7]	P	Italy	810	D	3	CI/BoD	CCR - I.	CW	No
Blancard and Hoarau [8]	DC	Global	122	D	4	CI/BoD	CCR – I	RC	No
Bougnol et al. [11]	C	Global	15	D	3	CI/BoD	CCR – I[b]	DR and clust	No
Carboni and Russu [12]	R	Italy	20	8	4	CI	BCC – O	MI	ANN
Chaaban [14]	C	Global	59	3	3	RSE and PCE	CCR – I	MI and UO	No
Cravioto et al. [23]	C	Global	40	2	1	PFE and PCE	CCR – I	No	No
Debnath and Shankar [25]	C	Global	113	4	2	RSE	BCC – O	No	No
Despotis [27] – *two analyses*	C	Asia and Pacific	27	D	3	CI/BoD	CCR – I	CW	No
				1	2	SE	BCC – I	No	No
Despotis [29] – *two analyses*	C	Global	174	D	3	CI/BoD	CCR – I	CW	No
				1	2	SE	BCC – I	No	No
Despotis et al. [30]	C	Global	174	D	3	CI/BoD	CCR – I	Not-linear virtual outputs and inputs	No
Domínguez-Serrano and Blancas [31]	C	Europe	27	D	4	CI/BoD	CCR – I	IF and CW	No
Fernández [35]	R	Spain and Italy	38	D	5	CI/BoD	CCR – I	RC	No
Friebelová and Friebel [36] – *two analyses*	R	Czech Republic	76	3	1	CI	CCR – O	No	Statistical analysis
				4	1	CI	CCR – O	No	Statistical analysis
Guardiola and Picazo-Tadeo [42]	P	Mexico	178	D	10	CI/BoD	CCR – I	CW	No
Golany and Thore [37]	C	Global	72	3	4	RSE	CCR – I and BCC – I	RE	No
González et al. [38]	M	Spain	643	8	11	CI	BCC – O	VEA and SupE	No
González et al. [39]	M	Spain	643	8	11	CI	BCC - O	VEA and SupE	No
González et al [40]	M	Spain	243	8	11	CI	BCC – O	VEA	No
Habibov and Fan [43]	R	Canada	10	4	2	RSE	CCR – I	CE and SupE	No
Hashimoto and Ishikawa [45]	M	Japan	47	4	4	CI	CCR – I	AR	No
Hashimoto and Kodama [46]	Y	Japan	35	4	4	CI	CCR – I	AR, CE and SA	No
Hashimoto et al. [47]	M	Japan	47	4	4	CI	CCR – I	IF and MI	No
Hatefi and Torabi [48] – *two analyses*	C	Asia and Pacific	18	D	3	CI/BoD	CCR – I	CW	No
			27	D	3	CI/BoD	CCR – I	CW	No
Jurado and Perez-Mayo [50]	R	Spain	17	D	15	CI/BoD	CCR – I	UO	Comparison with other methods
Lee et al. [53]	C	Asia and Pacific	27	D	3	CI/BoD	CCR – I	Multiobjective fuzzy model	No
Lefebvre et al. [54] – *two analyses*	C	Europe	15	D	5	CI/BoD	CCR – I	MI and SA	No
				1	5	RSE	CCR – I	No	No
Lopes and Camanho [58]	M	Europe	174	8	3	PCE	CCR – O	RS	No
Mahani et al. [59]	M	Iran	13	3	3	PCE	CCR[a] and BCC[a]	No	No
Mahlberg and Obersteiner [60]	C	Global	174	D	3	CI/BoD	CCR – O	AR	No
Malul et al. [62] – *two analyses*	DC and MDC	Global	91	D	2	CI/BoD	CCR – I	SupE	No
				1	2	PCE	CCR – I	SupE	No
Mariano and Rebelatto [63]	C	Global	101	1	10	SE	BCC – O	RC, SA and TI	Previous statistical analysis
Marshall and Shortle [64]	M	USA	N/D	4	4	CI	BCC – O	VEA and NDV	No
Martić and Savić [65]	R	Serbia	30	4	4	PFE	CCR – O	SupE and CE	No
Martín and Mendoza [66]	M	Canary Islands	87	9	11	CI	BCC – O	CE	No
Mizobuchi [68] – *four analyses*	C	OECD	34	D	11	CI/BoD	CCR – I	No	Statistical analysis
				1	11	PFE	CCR – I	No	Statistical analysis
				1	11	PFE	CCR – I	No	Statistical analysis
				2	11	PFE	CCR – I	No	Statistical analysis

Morais and Camanho [69] – *two analyses*	M	Europe	206	D	29	CI/BoD	CCR – I	RC and CW	No
				1	29	SE	BCC – O	DimR	No
Morais et al. [70]	M	Europe	246	D	39	CI/BoD	CCR – I	DimR	No
Murias et al. [71]	R	Spain	50	3	5	CI	CCR – I	RC	No
Ogneva-Himmelberger et al. [72]	BG	USA	5033	2	1	CI	CCR – I	No	PCA and statistical analysis
Põldaru and Roots [73]	M	Estonia	15	5	3	PCE	SBM/VRS	No	PCA
Poveda [75]	R	Colombia	32	D	4	CI/BoD	CCR – I	SupE	Statistical analysis
Raab et al [76]	UDC	Global	38	4	3	PCE	Additive/CRS	No	No
Ramanathan [77]	C	MENA	18	3	4	CI	CCR[a] and BCC[a]	MI	Statistical analysis
Reig-Martínez [79]	C	Europe and MENA	42	D	7	CI/BoD	SBM/CRS	Clust and CW	No
Shetty and Pakkala [84]	R	Indian	32	1	3	CI	DDF/VRS	SupE	DDF
Somarriba and Pena [85]	C	Europe	28	21	21	CI	BCC – O	RS	Comparison with other methods
Santana et al. [81] – *three analyses*	C	BRICS	5	3	1	PFE	BCC – O	IF and WA	No
				3	1	PFE	BCC – O	IF and WA	NO
				2	1	PFE	BCC – O	IF and WA	No
Tofallis [88]	C	Global	169	D	3	CI/BoD	Multiplicative/CRS[b]	No	CW with linear regression
Ulengin et al. [90]	C	Global	45	3	3	PCE	CCR – O	SupE	ANN
Viloria et al. [92]	Y	Venezuela	12	3	5	SE and RSE	CCR[a], BCC[a], DRS[a] and IRS[a]	MI	No
Vizcaíno and Fernández [93]	M	Galicia	53	6	4	CI	CCR – I	No	Distance DP2
Wu et al. [95]	C	OCDE	19	1	3	PFE	CCR – I	SupE	No
Zhou et al. [97]	C	Global	18	D	3	CI/BoD	CCR – I	RC and IF	No
Zhou et al. [98]	C	Asia and Pacific	27	D	3	CI/BoD	Multiplicative/CRS	RC and IF	No
Zhu [99]	M	Global	20	6	6	CI	BCC – I and CCR – I	Multiples approaches	No

ANN, artificial neural networks; *AR*, assurance region; *BG*, block groups; *BoD*, benefit of the doubt; *C*, countries; *CE*, cross-evaluation; *CI*, composite index; *Clust*, clustering; *CW*, common weights; *D*, dummy variable; *DC*, developing countries; *DDF*, direct distance function; *DimR*, restriction on the contribution of a dimension; *DR*, direct restriction; *IF*, inverted frontier; *M*, municipalities; *MDC*, more developed countries; *MI*, Malmquist Index; *NDV*, non-discretionary variable; *P*, people; *PCA*, principal components analysis; *PCE*, previous conditions efficiency; *PFE*, production factor efficiency; *R*, regions and provinces; *RC*, restriction on the relative contribution of a variable; *RS*, returns to scale; *RSE*, resource spending efficiency; *SA*, sensitivity analysis; *SE*, social efficiency; *SupE*, superefficiency; *UDC*, undeveloped countries; *UO*, undesirable outputs; *VEA*, value efficiency analysis; *WA*, Window Analysis; *Y*, years.

[a] It did not specify in detail the orientation used.

[b] Adapted model with an extra variable β.

Table 4 shows the classification of the 57 selected papers regarding these dimensions. The current situation concerning these five dimensions will be presented in the next subsections (Step 4), along with the main gaps and research opportunities in each one (Step 5).

4.1. Bibliometric analysis

The first dimension to be presented focus on the bibliometric analysis of the articles. Table 5 shows the quantity and the percentage of papers found separated by journal and by year of publication.

As seen in Table 5, publications relating to DEA and human development are highly concentrated in the SIR and SEPS journals, which hold 49.12% of the publications found. It is important to highlight that these two journals include in their scope researches on new methodologies to measure quality of life. A much smaller number of articles are found in journals addressing the field of operations research, such as OMEGA, EJOR and JORS, which concentrate 12.28% of publications It is worth noticing that the papers published in these journals often focus on new outlooks for the DEA technique, which are applied to social problems. The remaining 38.60% of articles are scattered in other journals and conference proceedings.

As for the year of publication, which can also be seen in Table 4, the first article that applied the DEA to evaluate the quality of life was the work of Hashimoto and Ishikawa [45], which was published over 20 years ago in the SEPS journal. In the 1990s, however, the subject had no major developments, and only two more articles were published in 1997. It must be observed that the last 5 years have concentrated 63.16% of the studies selected, demonstrating that this is a dynamic research area.

When it comes to identifying the most important works, a useful parameter to classify them is the number of citations. Nevertheless, it is important to remember that the most recent articles have not yet had time to become prominent in this regard. Table 6 shows the twenty most cited papers among the 57 selected ones, together with the number of citations in the Scopus and Web of Science databases in November 2014.

Table 5
Total number of papers by year and journal.

Analysis criteria	Classification	Quantity	Perceptual (%)
Journal	Social Indicators Research (SIR)	18	31.58
	Socio-Economic Planning Sciences (SEPS)	10	17.54
	Omega	3	5.26
	European Journal of Operational Research (EJOR)	2	3.51
	Ecological Economics (EE)	2	3.51
	Journal of the Operational Research Society (JORS)	2	3.51
	Others	20	35.09
Year	1993	1	1.75
	1997	2	3.51
	2000	1	1.75
	2001	3	5.26
	2005	3	5.26
	2006	4	7.02
	2007	1	1.75
	2009	6	10.53
	2010	9	15.79
	2011	9	15.79
	2012	2	3.51
	2013	8	14.04
	2014	8	14.04

Table 6
Twenty most cited papers among the 57 selected papers.

Research	Scopus citations	Web of Science citations
Despotis [29]	63	48
Despotis [27]	53	36
Zhou et al. [97]	51	37
Zhu [99]	41	It is not in this base
Hashimoto and Ishikawa [45]	29	23
Ramanathan [77]	29	It is not in this base
Zhou et al. [98]	28	24
Murias et al. [71]	27	20
Golany and Thore [37]	26	It is not in this base
Somarriba and Pena [85]	25	16
Martić and Savić [65]	25	15
Hashimoto and Kodama [46]	22	18
Morais and Camanho [69]	22	17
Hatefi and Torabi [48]	21	10
Bougnol et al. [11]	19	14
Raab et al. [76]	13	It is not in this base
Despotis et al. [30]	10	4
Adler et al. [1]	10	It is not in this base
Habibov and Fan [43]	9	6

Among the articles selected, the most cited were those of Despotis [27,29], which presented new ideas for using DEA in human development, such as the use of common weights and the proposal of social efficiency, and the one by Zhou et al. [97], which developed a new model for calculating composite indexes that was expanded in Zhou et al. [98]. It should be added that pioneering articles such as those of Zhu [99] and Hashimoto and Ishikawa [45] also show a high number of citations.

4.2. Scope of analysis

Regarding the scope of the analysis, the 57 selected papers are divided in two major groups: (a) those which used DEA to construct composite indexes (CIs); and (b) those which used DEA to evaluate the efficiency in generating quality of life, and this refers to (1) social efficiency (SE), related to the transformation of economic wealth into the quality of life and/or welfare and/or human development [63]; or (2) the economic-social efficiency (ESE), related to the process of generating these attributes from (i) previous social and environmental conditions (PCE), (ii) resources spent (RSE) and/or (iii) production factors (PFE). Fig. 1 graphically depicts these approaches.

According to Fig. 1, some types of analysis begin with the assumption that generating human development occurs in two different stages, in which some inputs are converted into wealth in the first stage, giving rise to the idea of economic efficiency (EE), and in the second stage that wealth is converted into quality of life, giving rise to the idea of social efficiency (SE). However, the economic-social efficiency (ESE) approach simplifies the analysis, directly associating productive inputs and quality of life in just one stage.

Another important point in Fig. 1 is that there is a feedback process, whereas the quality of life generated reinforces the productive inputs (human capital, for example), which in the future will generate economic wealth as well as quality of life [78,86]. However, the studies evaluating the economic efficiency and the feedback process were not part of the scope of this research.

In quantitative terms, most of the articles focus on building CIs, and of the 63 analyses, 40 (63.49%) can be classified in this category. It is noteworthy that the articles of Despotis [27,29], Malul et al. [62], Lefebvre et al. [54], Morais and Camanho [69] and Mizobuchi [68] addressed both building CIs and analyzing

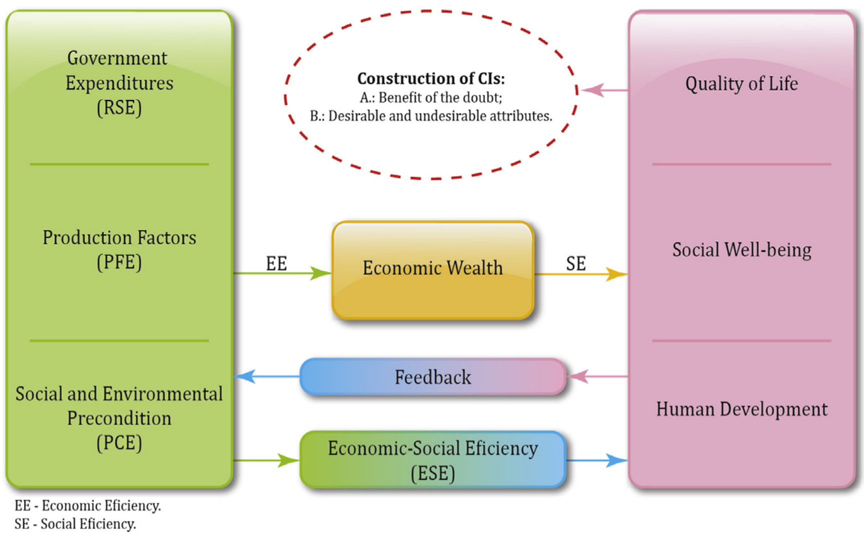

Fig. 1. Types of scope of analysis.

efficiency in generating quality of life; thus there are 63 different analyses in the 57 articles selected.

A CI can be defined as a synthetic index that condenses a series of indicators into a single value [10]. The great advantage of a CI is its simplicity, since complex and multidimensional issues such as quality of life can be assessed in an integrated manner. However, a CI must be constructed carefully, as it can often lead to wrong conclusions. In this sense, according to Booysen [10], the method for constructing a CI should consider the following procedures:

1. Selecting the indicators, which besides not being redundant should completely reflect the concept that one wants to measure.
2. Re-planning, the process of placing all the indicators in one measurement scale.
3. Weighting and aggregating, which is joining the indicators into a single index and assigning weights to each one of them.
4. Validation, which is evaluating the quality of the index developed.

The major advantage of DEA is the weighting of indicators within the CI, since the DEA allows extracting a set of weights from the data itself, which eliminates the arbitrariness in choosing them. In the work of Decancq and Lugo [26] eight approaches were listed to determine the weights in constructing CIs, with the DEA located within a category called 'most favorable weights'. Such designation can be explained by the fact that the DEA-based CIs often have the following characteristics:

1. The weights implemented for each indicator vary from unit to unit.
2. The weights used are the most advantageous for each unit.
3. The aggregation between indicators is done as a linear combination.
4. The index obtained is related to the units analyzed, ranging from 0 to 1 [77].

The DEA, however, allows alternative approaches, which enables, for example (a) incorporating the opinion of experts, through weight restrictions, which transforms it into a hybrid approach between arbitrary and endogenous [26]; (b) determining a common set of weights that is the most advantageous for all units [27,29]; and (c) performing a multiplicative aggregation of the indicators [98,88].

Also in terms of scope, an interesting point, illustrated in Fig. 1, is that there are two approaches to construct CIs using the DEA: (a) the benefit of the doubt (BoD), using only the desirable attributes; and (b) based on the ratio between desirable (more-the-better) and undesirable (less-the-better) performance measures [21]. The model with desirable and undesirable attributes was first used by Hashimoto and Ishikawa [45], which used it to build a quality of life index for Japan.

The BoD model, originally proposed by Melyn and Moesen [67] and revised in depth by Cherchye et al. [19], is based on implementing DEA with the indicators (outputs) being all grouped into a single index, along with a dummy input equal to 1. According to De Witte et al. [24], BoD differs from the standard DEA-model because it exclusively focuses on aggregating outputs. Recent articles that presented advances in the BoD model are Färe and Karagiannis [34] and De Witte et al. [24]. Among the 57 articles assessed, Mahlberg and Obersteiner [60] were the first to use this approach, using it to recalculate the HDI.

The number of analyses performed with both approaches was close in quantitative terms. Among the 40 assessed articles, 23 (57.50%) used the BoD model and 17 (42.50%) the model with inputs and outputs. Considering these two approaches, the first gap regarding the use of DEA was identified in the analyses of human development, namely:

G_1 : What are the advantages and disadvantages of CIs built from the BoD model or the model with desirable and undesirable attributes?

Regarding the analysis of efficiency in generating quality of life, whose bases are in Fig. 1, different types of approaches should be defined, such as (a) social efficiency (SE), which uses economic wealth as input; (b) efficiency of government resources spent (RSE); (c) efficiency from previous social and environmental conditions (PCE); and (d) efficiency of production factors (PFE), as capital and labor. Table 7 shows the number of analyses, out of 23 analyzed articles, for each type of approach.

As seen in Table 7, four papers used inputs classified into different groups, which may have prevented interpreting the results. Accordingly, a more consistent analysis could be achieved if all these types of approaches were to be performed simultaneously in separate analyses, in order to build a more comprehensive outlook in terms of efficiency

Table 7
The number of papers for each type of approach.

Scope	Quantity	Perceptual (%)
PCE	6	26.09
RSE	5	21.74
PFE	4	17.39
SE	4	17.39
SE and RSE	2	8.70
PFE and PCE	1	4.35
RSE and PCE	1	4.35
Total	**23**	**100**

in generating quality of life. This joint evaluation of different scopes of analysis is the second gap identified, namely:

G_2 : Performing a joint and integrated analysis of the situation of a country, a city or region taking into account the different types of social and socioeconomic efficiency defined.

4.3. DEA approaches

In this section we analyze the main DEA approaches used in the 57 articles assessed. Thus, the following will be addressed: (a) the models used; (b) the extensions of these models; and (c) the interfaces with other techniques.

4.3.1. Models

Regarding the DEA approaches, the models must first be analyzed. The first observation about them was the fact that the construction of CIs by the benefit of the doubt – BoD approach usually uses, with rare exceptions, the CCR input oriented model (CCR – I), which is the case for 18 (78.26%) of the 23 analyses performed. We also point out to the fact that the five other papers that used the BoD approach also used constant returns to scale, but they did not use the CCR – I, whereas (a) Zhou et al. [98] and Tofallis [88] used a multiplicative DEA model; (b) Reig-Martínez [79] used the SBM model; (c) Bougnol et al. [11] proposed an adaptation of the CCR – I model, with the accretion of a variable β, but it did not present any advantage of this adaptation; and (d) Mahlberg and Obersteiner [60] used the CCR output oriented model.

The reason why the CCR-I model predominates is that it helps to understand the BoD approach without prior knowledge of the DEA, which brings it closer to the original model proposed by Melyn and Moesen [67]. This shows the lack of studies that use non-radial models for constructing CIs, whereas only the recent work of Reig-Martínez [79] can be included in this category. This lack of studies in a seemingly promising field enabled us to identify the third and fourth gaps seen in the analyses, namely:

G_3 : The lack of CI construction studies based on non-radial models, such as SBM and the Russell Measure Model.

G_4 : The absence of studies comparing advantages and disadvantages of CIs based on radial and non-radial models.

The multiplicative models in Zhou et al. [98] and Tofallis [88] were presented in order to adapt the BoD methodology to the new method of calculating HDI, which is based on geometric means. As well as the model of Bougnol et al. [11], the model of Tofallis [88] presents an extra variable β, but the justification, in this case, is making the model scale invariant. We highlight that the major advantage of indexes based on geometric means is that it does not require that the aggregated indicators have to be perfect substitutes for each other [88], which is more in line with reality. With this in mind, additional analyses of this type could have been performed, characterizing this as the fifth gap regarding this matter, namely:

G_5 : The lack of more CIs based on multiplicative DEA models.

As for the CIs based on desirable and undesirable attributes, there was no consensus on which is the best model to be used, in such a way that among the 17 analyses identified, six used the CCR – I model (35.29%), one a CCR – O model (5.88%) and seven the BCC – O model (41.18%). Apart from these, the study of Shetty and Pakkala [84] used variable returns to scale through an approach with directional distance function – DDF; and the works of Ramanathan [77] and Zhu [99] performed a comparative analysis, which did not provide details of both types of returns. Considering these results, it can be stated that approximately half of the analyses of this type used constant returns to scale and the other half used variable returns to scale, which allows us to identify the sixth gap:

G_6 : What is the relevance, advantages and disadvantages of using variable or constant returns to scale in the construction of CIs from the desirable and undesirable attributes approach?

It is also important to notice that there is a great variety of models being used in the 23 studies about efficiency in generating quality of life. All four studies on social efficiency (SE), for example, used the BCC model, with two of them oriented to input and two oriented to output. This was a reasonable choice, since it is quite likely that economic growth does not proportionally generate social benefits; however, this orientation makes more sense if it is directed towards outputs, since there is more logic in increasing quality of life than in reducing the GDP.

However, studies about economic-social efficiency (ESE), independently of the inputs used, show a predominance of models with constant returns to scale. Thus, of the 17 analyses performed, 10 (58.82%) used only the CCR model, two (11.76%) used only the BCC model and three (17.65%) used the CCR and BCC models jointly. The remaining two analyses, despite using variable returns to scale, varied regarding the model used, as follows: (a) Raab et al. [76] used the additive model; and (b) Põldaru and Roots [73] used the SBM model.

We highlight that the two papers that mixed SE with ESE either used the BCC model, as for instance Adler et al. [1], or all radial models, namely the CCR, BCC, DRS and IRS, as for instance Viloria et al. [92]. Considering all this information, we have the seventh gap about this type of analysis.

G_7 : Confirming the best type of returns to scale to be used in the approaches of social efficiency (SE) and economic-social efficiency (ESE).

The diversity of models used in the applications presented in this section corroborate the argument of Cook et al. [21] that little attention is paid to important modeling issues, as the choice of the model and the orientation. According to these authors, it is crucial that the DEA community has an open mind about these issues.

4.3.2. Extensions

Several DEA extensions were used in the articles assessed, with different functions. One of the most used types of extension were those that allow incorporating the opinion of experts into the analysis, which includes inserting the weight restrictions, used in 17 articles (29.82%), and the VEA technique, used in four articles (7.02%) of the 57 selected articles.

Among the 17 studies that incorporated weight restrictions, the most common type was the restriction that limits the relative contribution (percentage) of a variable, used in nine articles (52.94%). This predominance can be explained by the fact that this type of restriction in the analysis of human development, especially regarding the construction of CIs, lends itself to easy interpretation. Other analyses that used weight restrictions applied region security restrictions (five articles – 29.41%) and direct restrictions (one article – 5.88%). In addition to these, the articles of Morais and Camanho [69] and Morais et al. [70] imposed limits on the relative contribution that each social dimension should have in the index that was built; it is noteworthy that each dimension was composed of a group of variables that did not have their weights restricted.

As for the VEA technique, used by Marshall and Shortle [64], González et al. [40] and González et al. [38,39], instead of establishing weight limits, one must choose, from among the units considered efficient by the standard DEA, the most preferred solution (MPS), which must be selected by experts. Once this is done, the VEA will examine the units based on the MPS, so that the most similar units will have higher indices.

It should be emphasized, however, that a structured technique, such as a survey or a panel of experts, was not used in any article to assign weight restrictions or the MPS, both of which were chosen arbitrarily. This fact constitutes the eighth gap identified:

G_8 : Using structured methods to set, based on the opinion of experts, the weight restrictions or the preferred solution (MPS).

In a second type of extension, we observed that DMU tie-breaking methods were used in 14 papers (24.56%). These methods are particularly important due to the fact that the DEA can often lead to multiple DMU ties, especially when working with many variables. It is worth mentioning that in the works of Hashimoto and Ishikawa [45] and Martić and Savić [65] two different tie-breaking methods were used, totalizing 16 analyses found in 14 articles.

Among the tie-breaking approaches used we highlight super-efficiency (seven analyses – 43.75%), inverted frontier (five analysis – 31.25%) and cross-evaluation (three analyses – 18.75%); the combination of these three methods, resulting in the Triple Index, was used in Mariano and Rebelatto [63]. It should be emphasized, however, that despite the predominance of super-efficiency, none of the articles established a protocol or gave any definitive justification for the use of some tie-breaking methods in the human development analyses, which is the ninth gap identified:

G_9 : Assessing the impact of tie-breaking methods for constructing CIs and assessing the efficiency in generating quality of life.

In terms of the treatment of panel data, which was used in 10 of the 57 (10.57%) articles assessed, whereas; (a) the Malmquist Index (MI) was used in six of them; (b) the Window Analysis (WA) was used only by Santana et al. [81]; and (c) in the works of Adler et al. [1], Bollou et al. [9] and Põldaru and Roots [73] all the years were combined in the same analysis, which presupposes, inappropriately, that technology does not change with time. The lack of use of structured temporal analysis methods, such as the Malmquist Index and the Window Analysis, is the 10th gap identified:

G_{10} : The lack of use of structured methods for analyzing panel data, such as the use of Window Analysis and the Malmquist Index.

Other extensions, which were used in only a few articles, can be highlighted given that they enable more specific analyses – cited as follows:

- The DEA-based clustering allows grouping units with common performance, which was used by Bougnol et al. [11] and Reig-Martínez [79].
- The inclusion of non-discretionary variables, which were used by Marshall and Shortle [64].
- The use of non-linear virtual outputs and inputs, as proposed by Despotis et al. [30], in order to recalculate the HDI.
- The determination and analysis of returns to scale, which was performed in the article of Golany and Thore [37].
- Sensitivity analyses, conducted by Mariano and Rebelatto [63], Lefebvre et al. [54] and Hashimoto and Kodama [46].

Finally, an extremely important topic in this type of analysis is the approaches that strive to find the most advantageous set of common weights, on average, for the DMUs. Thus, it should be noted that this set of weights can be found with DEA extensions, which include approaches based on linear programming based on auxiliary techniques, as well as linear regression, which will be commented in the next section.

With this clarification, it can be stated that the first work to focus on the need to establish common weights to build CIs was Despotis [27,29], who proposed a multi-objective model based on linear programming and used it as a second stage for the DEA technique. Thus, the model of Despotis [27,29] first requires applying the standard DEA, whereas the indices achieved (CI_j) will be used as input variables in the second stage. Considering the deviation concept (d_j) as the difference between the CI_j and the index achieved with ordinary weights, it can be said, as illustrated by Model 1, that the second stage is based on minimizing a weight (adjusted by the parameter t) between (a) the average of the deviations and (b) the largest deviation achieved (z)

$$\begin{aligned} &\min \frac{t}{n} \times \sum_{i=1}^{n} d_j + (1-t) \times z \\ &\sum_{i=1}^{m} w_i \times I_{ij} + d_j = CI_j, \ \forall j \\ &d_j - z \le 0, \ \forall j \\ &w_i, d_j, z \ge 0, \ \forall i \text{ and } \forall j \end{aligned} \tag{1}$$

where

w_i common weight of the indicator i;
I_{ij} indicator i of unit j;
d_j deviation between the index obtained with common weights and the index given by the standard DEA;
z largest deviation d_j;
CI_j index obtained with the application of standard DEA in the first stage of unit j;
n number of units analyzed;
m number of indicators that comprise the CI; and
t parameter that regulates how much each minimization function will contribute.

Despotis [27,29] suggests that several t values should be tested in order to find the best solution of common weights for each range of t values. Domínguez-Serrano and Blancas [31] proposed that the average of the CIs found with all ranges of t be adopted.

Along this same line, six studies are cited: (1 and 2) Morais and Camanho [69] and Reig-Martínez [79], which used the original model of Despotis [27,29]; (3) Hatefi and Torabi [48], which proposed a model based only on minimizing the largest deviation ($t=0$); (4) Bernini et al. [7], based solely on minimizing the mean of the deviations ($t=1$); (5) Guardiola and Picazo-Tadeo [42], which compared the approaches with $t=0$ and $t=1$; (6) Domínguez-Serrano and Blancas [31], which extended the model of Despotis [27,29] and presented a model of common weights based on the inverted frontier; (7) Lee et al. [53], which incorporated a Fuzzy logic-based approach into the model.

4.3.3. Interfaces with other techniques

A considerable range of analyses on human development can be achieved by integrating DEA with other techniques, which is a trend in recent articles. Of the 57 papers assessed, 15 (26.32%) carried out this integration and 16 analyses were conducted, since the work Ogneva-Himmelberger et al. [72] has used two different approaches. These interfaces are divided into three categories: (a) ex-ante (37.50% of the analyses), which use auxiliary techniques before applying the DEA; (b) ex-post (50.00% of the analyses), which use auxiliary techniques after applying the DEA; and (c) comparative (12.50% of the analysis), which compare the DEA with alternative analysis techniques.

Of the articles that use ex-ante techniques, we highlight three that used the principal components analysis (PCA) technique: Ogneva-Himmelberger et al. [72], Adler et al. [1] and Põldaru and Roots [73]. The goal of the PCA, used together with the DEA, is to improve the quality of the CI, avoiding to add variables that are too correlated with each other. The PCA allows transforming highly correlated variables into a set of independent variables, which contain the same original information, but with a certain level of loss. The next two gaps derive from this approach.

G_{11} : Determining to what extent avoiding redundancies compensates for the loss of information when using the DEA-PCA.

G_{12} : Determining the maximum tolerable level of loss of information so that the CI obtained by DEA-PCA is still useful.

Another type of ex-ante analysis consists of using auxiliary techniques to select variables, which was done by Vizcaíno and Fernández [93] with the P_2 distance technique. Mariano and Rebelatto [63], on the other hand, used linear regression to determine the best time lag between the inputs and outputs. Also as an example of ex-ante application, Shetty and Pakkala [84] used the directional distance function (DDF), which is a DEA derived technique in order to calculate an alternative index for the HDI; as a guiding function they used the same weights of the original HDI.

As for the ex-post analyses, the first to be mentioned is the common weights approach based on linear regression, used by Tofallis [88] and based on the fact that the regression based on ordinary least squares (OLS) is also a function that minimizes deviations, but squared. Thus, when setting the efficiencies obtained with the DEA to a straight line, the function coefficients will be the most advantageous common weights for the units.

In terms of statistical analysis of the results: (a) the work of Ramanathan [77] should be highlighted, since it performed the regression of a quality of life index built with the DEA in terms of population and GDP per capita of each country; (b) Poveda et al. [75] performed the regression of the index constructed in terms of nine explanatory variables using panel data; (c) Friebelová and Friebel [36] used an analysis of differences between means, separating the units by efficiency ranges to analyze the impact of the amount of liquid migrations on the quality of life; (d) Ogneva-Himmelberger et al. [72] used linear regression to evaluate the impact of four environmental variables on the CI constructed; and (e) Mizobuchi et al. [68] used a correlation matrix to analyze the relationship between income, HDI and four indexes constructed by him.

In a non-statistical ex-post approach, Ülengin et al. [90] used artificial neural networks (ANN) to determine which inputs and outputs had the most significant impact on the efficiency in converting competitiveness into human development, and Carboni and Russu [12] used the ANN called the self-organization map to cluster the DMUs analyzed.

Finally, there are two comparative studies: (a) Somarriba and Pena [85] which compared DEA with the P_2 distance and PCA techniques; (b) and Jurado and Perez-Mayo [50], which compared DEA with the Factor analysis technique. It is worth noting that Somarriba and Pena [85] concluded that the P_2 distance method has advantages over the other two techniques compared; Jurado and Perez-Mayo [50] concluded that the two compared techniques have quite correlated results. The example of the comparative analysis carried out in these works reveals another gap identified.

G_{13} : Comparing the advantages and disadvantages of DEA with the alternative techniques for building CIs.

4.4. Units analyzed

In this section the units assessed in the 57 articles collected will be analyzed. In this regard, Table 8 shows the number of analyses found and classified in two dimensions: type and economic/geographic region. We underline that for estimating the geographic or economic region, 59 analyses were considered, since there were two articles that combined two regions in their analysis: (a) Reig-Martínez [79], which analyzed Europe and MENA (Middle East and North Africa); and (b) Fernández et al. [35], which analyzed Spain and Italy.

According to Table 8, 29 (50.88%) of the selected 57 articles presented country analyses. One possible reason is the fact that these analyses have abundant information, which is available in the databases of the World Bank, PUNUD, UNESCO, CIA, among others.

Of these 29 articles, 16 had a global geographic reach; among these, the articles of Raab et al. [76], Malul et al. [62], Blancard and Hoarau [8] and Adler et al. [1] only analyzed countries with common socioeconomic classification, that is developed, underdeveloped and in development. Quantitatively, the studies that came closest to a comprehensive analysis were the articles of Mahlberg and Obersteiner [60], Despotis [29] and Despotis et al. [30] which analyzed 174 countries. These articles, however, delimited their scope to HDI dimensions, and the inclusion of other social indicators inevitably results in leaving out the countries analyzed, which in turn is the 13th gap identified:

G_{14} : Increasing the number of global analyses with the inclusion of a higher number of countries without neglecting the variables analyzed.

The 13 non-global country analyses are focused in five specific geographic/economic regions: Europe (four papers), Asia and

Table 8
The number of papers found and classified by type and geographic region.

Analysis criteria	Classification	Quantity	Perceptual (%)
Type	Countries	29	50.88
	Municipalities	14	24.56
	Regions	9	15.79
	Years	2	3.51
	People	2	3.51
	Block group	1	1.75
	Total	**57**	**100**
Geography or economic region	Global	17	28.81
	Europe	7	11.86
	Asia and Pacific	4	6.78
	Spain	6	10.17
	Japan	3	5.08
	Italy	3	5.08
	MENA	2	3.39
	USA	2	3.39
	OECD	2	3.39
	Africa, BRICS, Canada, Colombia, Estonia, Galicia, Canary Islands, Iran, India, Czech Republic, Serbia Mexico and Venezuela	1 (× 13)	1.69 (× 13)
	Total	**59**	**100**

Table 9
The quantification of the major social terms used in the 57 papers.

Social term	Quantity	Perceptual (%)
Quality of life	17	29.31
Human development	15	25.86
Well-being	4	6.90
Economic well-being	2	3.45
Social welfare	2	3.45
Sustainable energy	2	3.45
Better life; economic and social performance; economic development; economic, environmental and social efficiency; happiness; life satisfaction; livability; social and economic development; social performance; social protection; socio-economic performance; state of society; subjective community well-being; sustainable human development; sustainable development; welfare	1 (× 16)	1.72 (× 16)
Total	58	100

Pacific (four papers), MENA (two papers), Organization for Economic Co-operation and Development – OECD (two papers), Africa (one paper) and BRICS (one paper). The key advantage of the analyses which focused on a socioeconomic group of countries or a specific geographic region is that they ensure slightly more homogeneous DMUs, which can lead the DEA to more reliable results.

The second group of the 57 papers assessed was divided between the analysis of various types of DMUs, with a predominance of analyses related to Municipalities (24.56% of the analyses) and regions (15.79% of the analyses). In these papers the use of a wider range of indicators is often simpler, as illustrated in Morais and Camanho [69], which analyzed 246 European cities using 39 indicators.

A source of analysis that could still be further explored regards building indices for interpersonal comparisons, since only the recent studies of Guardiola and Picazo-Tadeo [42], Bernini et al. [7] and Ogneva-Himmelberger et al. [72], which correspond to 5.26% of the articles, can be included in this type of analysis. It is noteworthy that Ogneva-Himmelberger et al. [72] used a unit of analysis called the Block Group, which covers a set 600–3000 people. This lack of studies with interpersonal comparisons, which are usually based on surveys conducted by the researcher, is the next gap identified, namely:

G_{15} : There is a lack of studies that use DEA to analyze data from interpersonal comparison studies, usually conducted through surveys.

Specifically regarding the geographical scope of the DMUs analyzed, it is perceived that there is a great deal of focus on Europe, which was the topic of 11.86% of the analyses. Aside from this, a series of analyses were performed within specific European countries, with the greatest focus on Spain, which was the topic of 10.17% of the analyses. We then conclude that many regions such as Latin America and Africa lack specific social analysis, as illustrated by the next gap identified, namely:

G_{16} : More analyses related both to countries and to regions and focusing on Africa and Latin America are needed.

4.5. Depth of analysis

This section will evaluate the extent of the papers selected in relation to the characterization and social analysis. The results are initially presented with the analysis of the social term used to characterize the research, evaluating the chosen social dimensions.

Table 10
Social dimension and its definition.

Social dimension	Variables
Climatic conditions	Average temperature. Average number of days without rain. Relative humidity of the air, etc.
Cost of living	Price per square meter. Cost of right product. Rate of inflation, etc.
Demographics	Fertility rate. Population density. Population growth. Composition of families, etc.
Economy	Income. Consumption. GDP growth. GDP per capita. Accumulation. Economic vulnerability. Business environment, etc.
Education	Average years of schooling. School life expectancy. Enrollment rate. Literacy. Human capital indicators of educational quality. Nor study and not work people, etc.
Environment	CO_2 emissions. Climate change. Carbon footprint. Energy consumption. Total green areas. Street cleaning, etc.
Happiness	Subjective well-being. Life satisfaction. Confidence
Health	Number of doctors. Suicide rate. Life expectancy. Infant mortality. Number of hospital beds. Malnutrition rate. Mortality rate. Sedentary, etc.
Housing	Housing deficit. Satisfaction with home and the place where you live. Size of residence. Physical conditions of residence, etc.
Inequality	Indices of income inequality and gender inequality.
Leisure	Number of museums. Number of libraries. Number of entertainment establishments. Leisure time. Sports. Culture facilities, etc.
Poverty	Population living below the poverty line.
Security	Level of crime. Homicides. Number of police. The number of violent crimes. Problems with drug trafficking, etc.
Social life	Satisfaction with social life. Satisfaction with love. Number of contacts. Satisfaction with family. Political participation. Involvement in public life. Quality of the communication system, etc.
Social protection	Social insurance. Unemployment insurance. Pensions. Quality of public services, etc.
Transportation	Time of journey to work by car. Traffic density. Quality public transport, etc.
Work	Number of jobs. Level of satisfaction with their jobs. Unemployment, etc.

Table 11
The most explored dimensions in the 57 papers.

Social dimension	Quantity of papers	Perceptual (%)
Economy	49	85.96
Health	38	66.67
Education	35	61.40
Environment	20	35.09
Work	18	31.58
Security	15	26.32
Leisure	13	22.81
Housing	11	19.30
Inequality	10	17.54
Social life	9	15.79
Poverty	8	14.04
Transportation	5	8.77
Social protection	5	8.77
Cost of living	4	7.02
Demographics	4	7.02
Happiness	4	7.02
Climatic conditions	2	3.51
Total	**57**	**100**

Table 12
The number of variables that was used in each study.

Number of variables	Quantity		Perceptual	
	Input	Output	Input (%)	Output (%)
1	10	7	14.49	10.14
2	4	6	5.80	8.70
3	10	21	14.49	30.43
4	11	12	15.94	17.39
5	1	5	1.45	7.25
6	2	1	2.90	1.45
7	0	1	0.00	1.45
8	5	0	7.25	0.00
9	1	0	1.45	0.00
10	0	3	0.00	4.35
>10	1	13	1.45	18.84
Dummy	24	0	34.78	0.00
Total	**69**	**69**	**100.00**	**100.00**

Lastly, we will analyze the number of variables used – such as inputs and outputs.

Table 9 shows the quantification of the major social terms used in the 57 articles (two articles used two different terms). We emphasize that only the main term was quantified, thus, the specifications relating to specific groups such as children, young people or women were not counted separately.

As seen in Table 9, 22 different social terms were used in the articles; moreover, although some of these represent different concepts, and despite the difference in spelling, many are closely related or identical. As the search engines in scientific databases are case sensitive, there is a lack of research in establishing a uniformity of the social terms used. This gap is the sixteenth gap identified, namely:

G_{17} : Determining a standardized vocabulary or language for the area of human development.

A consequence of the lack of standardization of social terms is due to the absence of consensus about the social dimensions that should be used. For the purposes of this work, a social dimension can be defined as a grouping of variables that have an impact on the same area. An example is the social dimension ‘ education’, which could cover a number of variables, such as average years of schooling, enrollment rate, literacy rate, level of performance on math tests, among others. This lack of clarity about the social dimensions is another gap to be explored:

G_{18} : Developing a taxonomy to represent a set of homogeneous dimensions to be used in social studies; the main variables included in each dimension should be defined.

Despite the gap, to continue the analysis, it was necessary to define a set of dimensions in order to classify the articles. It should be mentioned that if we followed the taxonomy of dimensions established in every article, it would not be feasible to quantify them, due to the aforementioned heterogeneity. Thus we emphasize that this definition does not intend to eliminate this gap, as we only used a set of dimensions to facilitate the analysis of the 57 articles assessed. Table 10 presents the 17 dimensions chosen.

After the articles were classified and analyzed, it was possible to identify and quantify the social dimensions that were used in

Table 13
The summary of each 57 papers analyzed in this study.

Research	Description	Social term	Social dimensions	Contributions
Hashimoto and Ishikawa [45]	Socially evaluated of 47 Japanese cities	State of society	Economy, housing, environment, health and security	Method for construction of social indicators based on desirable and undesirable attributes
Golany and Thore [37]	Evaluated the returns to scale from 72 countries in converting investment and government spending into social benefits	Social performance	Economy, education, social protection and health	Approach to evaluate the efficiency and scale of public spending and private investment
Hashimoto and Kodama [46]	Assessed the social evolution of Japan between 1956 and 1990	Livability	Health, security, environment, economy and work	Method to compare different periods.
Raab et al. [76]	Evaluated the efficiency of underdeveloped countries in providing, through their preconditions, child quality of life	Child quality of life	Education and health	Approach to evaluate the efficiency in providing child quality of life focusing on developing countries
Martić and Savić [65]	Evaluated the efficiency of 30 regions of Serbia in using factors of production to generate economic and social well-being	Social and economic development	Health, economy and education	Approach to assess the economic and social efficiency of production factors
Mahlberg and Obersteiner [60]	Proposed a new approach to measure HDI and evaluated 174 countries	Human development	HDI - economy, health and education	Use the DEA to calculate the HDI through the model of the Benefit of the Doubt - BoD
Zhu [99]	Evaluated the quality of life of the 20 best cities to live by Fortune magazine	Quality of life	Cost of living, economy, leisure and security	He proposed five different assessment of quality of life from the DEA approaches
Despotis [27]	Proposed new ways to calculate the HDI and evaluated countries in Asia and the Pacific	Human development	HDI - economy, health and education	Developed two new possibilities for using DEA in the calculation of HDI: (a) the common weights model and (b) the transformation paradigm (social efficiency)
Despotis [29]	Extended their previous work by assessing 174 countries	Human development	HDI - economy, health and education	
Marshall and Shortle [64]	Evaluated the quality of life of cities in the mid-Atlantic region of the United States	Quality of life	Education, economy, leisure, environment and poverty	Compared the DEA and VEA techniques to assess quality of life in urban and rural cities
Murias et al. [71]	Created a synthetic economic well-being index to evaluate 50 Spanish provinces	Economic wellbeing	Economy, poverty, work and inequality	They used only social indicators derived of the economic situation; compared the index with GDP per capita
Lee et al. [53]	Proposed a new method of calculating the HDI to evaluate countries in Asia and the Pacific	Human development	HDI - economy, health and education	Method based on fuzzy logic to calculate the HDI with common weights
Bollou et al. [9]	Evaluated the impact of investments in communication, health and education on human development in African countries	Human development	HDI - economy, health and education	They made a longitudinal analysis (7 years) with emphasis on the influence of public spending on communication
Ramanathan [77]	Evaluated the social and economic performance of MENA countries between 1997 and 1999, and examined two explicative factors	Economic and social performance	Health, economy, work and education	Pioneered the use of Malmquist index and the explanatory factors test Stressed the importance of considering gender differences
Zhou et al. [97]	Evaluated the energy sustainability with a new method for building composite indexes	Sustainable energy	Environment	Method of construction of composite indices derived from the BoD model and inverted frontier
Somarriba and Pena [85]	Evaluated the quality of life of 28 countries, using three techniques. Performed a comparative analysis between them	Quality of life	Housing, economy, social life, education, work and happiness	Comparison of DEA with distance *P*2 and Principal Component Analysis (PCA). First to incorporate happiness in the analysis
Malul et al. [62]	Analysis of 91 countries, which involved the construction of an index and the evaluation of the efficiency in the use of natural resources	Economic, environmental and social efficiency.	Economy and inequality	Evaluation of the efficiency and efficacy of social countries with a focus on income inequality; split developed and developing countries
Chaaban [14]	Evaluated the efficiency of 59 countries in providing through their social conditions and resources, youth welfare	Youth welfare	Work, demographics and education	Focused on youth and the use of the Malmquist index to check the evolution of efficiency
Hashimoto et al. [47]	Analyzed the changes in the quality of life of Japanese cities between 1975 and 2002	Quality of life	Health, security, environment and economy	Conducted a temporal and spatial analysis of the quality of life by using inverted frontier and Malmquist index
Viloria et al. [92]	Analyzed the evolution of the efficiency of Venezuela in converting social spending and GDP per capita on social welfare	Social welfare	Education, poverty, health, economy and work	Used the Malmquist index to evaluate the evolution of the efficiency of Venezuela and made a parallel analysis based only on economic aspects
Vizcaíno and Fernández [93]	Evaluated the quality of life of cities in Galicia	Quality of life	Economy, education, health, work, leisure, social life and transportation	Used the distance *P*2 to select the variables that would be present in the index of quality of life
Zhou et al. [98]	Proposed a multiplicative approach to evaluate the HDI of 27 countries in Asia and the Pacific	Human development	HDI – economy, health and education	Adapted the model developed in Zhou et al. [97] to the new method of calculating the HDI, which uses geometric mean
Bougnol et al. [11]	Developed a new model of calculating the HDI, applying it to the evaluation of 15 countries	Human development	HDI – economy, health and education	Created a model derived from the BoD, but with an extra variable. Pioneered in the use of DEA to cluster countries
Despotis et al. [30]	Proposed a DEA model with nonlinear virtual inputs and outputs	Human development	HDI – economy, health and education	Obtaining a model that eliminates the need to work with the logarithm of per capita income in the HDI
Hatefi and Torabi [48]	Proposed a new model to calculate composite indices and applied it in calculating the HDI and Sustainable Energy Index	Human development and sustainable energy	Environment and HDI	Proposed two models based on Multiple Criteria Decision Analysis (MCDA) aiming at finding common weights and tiebreaker

Table 13 (*continued*)

Research	Description	Social term	Social dimensions	Contributions
Shetty and Pakkala [84]	Calculated the HDI of Indian states using directional distance function (DDF)	Human development	HDI – economy, health and education	Pioneers in using DDF. It used in combination with the super-efficiency
Habibov and Fan [43]	Evaluated the efficiency of Canadian provinces in turning government expenses into income transfer programs for reducing poverty	Social welfare	Poverty	Evaluation of the effectiveness in the implementation of social programs to transfer income. Focus on poverty
Fernández et al. [35]	Compared the economic well-being of 38 regions in Italy and Spain	Economic well-being	Economy, work, education and inequality	Analysis of the contribution of each variable to group the cities. Comparison of the average well-being among Spanish and Italian cities.
Adler et al. [1]	Estimated the relative efficiency of developing countries in the use of its internal and external resources in achieving the Millennium development goals	Socio-economic performance.	Health, poverty, education and inequality	Compared the efficiency with the geographic region, financial situation and the human rights of countries. Pioneer in using PCA in an ex-ante analysis
Lefebvre et al. [54]	Constructed an index that assesses the social protection of 15 European countries and analyzed the evolution of this index	Social protection	Poverty, economy, education, inequality, health and work	Analyzed the efficiency of the social protection. Compared indices obtained from different forms of standardization. Used Malmquist index used to assess progress
Cravioto et al. [23]	Evaluated the effectiveness of 40 countries in converting energy consumption and the CO_2 emissions into HDI	Well-being	HDI – economy, health and education	Used the HDI as output and environmental indicators as input. A prior analysis was done to choice the variables
Morais and Camanho [69]	Used the DEA to evaluate the quality of life and social efficiency of 206 European cities	Quality of life	Demographics, economy, social life, cost of living, housing, leisure, environment and security	Responsible for the largest range of social indicators used. Proposed policies to improve the quality of life
Domínguez-Serrano and Blancas [31]	Constructed an index of well-being separated by gender to assess European countries	Gender well-being	HDI – economy, health and education	Method for construction of composite indices, which blends common weights and inverted frontier. Emphasis on genre analysis
Poveda [75]	Assessed the economic development of 23 regions of Colombia	Economic development	Economy, poverty, security and inequality	Conducted a regression with panel data in an attempt to explain economic development
González et al. [38]	Analyzed previous results in geographical and political-administrative terms	Quality of life	Economy, housing, transportation, social protection, work, environment, leisure, security and social life	Analyzed the quality of life. Considering the geographical and political-administrative influence
González [39]	Evaluated 643 Spanish cities	Quality of life	Economy, housing, transportation, social protection, work, environment, leisure, security and social life	Expanded their work with the use of super-efficiency
González et al. [40]	Evaluated 243 Spanish cities	Quality of life	Economy, housing, transportation, social protection, work, environment, leisure, security and social life	Use of VEA technique and comparison with DEA
Friebelová and Friebel [36]	Used the DEA to construct an index of quality of life in regions of the Czech Republic	Quality of life	Economy, environment, cost of living and security	They conducted analyzes with and without the input " price per square meter built" Compared the result of the index with the ranking of internal migration
Ülengin et al. [90]	Studied the impact of competitiveness of nations on the HDI using DEA and Artificial Neural Networks (ANN)	Human development	HDI - economy, health and education	Evaluated the relationship between human development and competitiveness. ANNs used to assess the contribution of the variables analyzed in the index obtained
Jurado and Perez-Mayo [50]	Constructed an index of welfare for regions of Spain and rated their evolution	Well-being	Economy, climatic conditions and inequality	Compared the results of DEA with the factor analysis
Mahani et al. [59]	Measured the efficiency of cities of Iran in generating HDI	Human development	HDI – economy, health and education	For each of the dimensions of the HDI selected a possible input generator
Lopes and Camanho [58]	Evaluated the efficiency of the relationship between quality of life and use of public spaces in 174 European cities	Quality of life	Security, environment, demographics and health	First to use the DEA to analyze the conversion of the use of public spaces in quality of life
Tofallis [88]	Evaluated the HDI for 169 countries with a new multiplicative approach	Human development	HDI – economy, health and education	Proposed a new multiplicative DEA model. Used an approach of common weights based on linear regression. Analyzed the HDI obtained with normalized and raw data
Bernini et al. [7]	Constructed an indicator of subjective well-being and used the results to find the main determinants of this indicator	Subjective community well-being	Social life, economy, work, leisure, health, security and environment	Used a DEA model with common weights to build a subjective well-being indicator
Blancard and Hoarau [8]	Evaluated the sustainability of 32 SIDS (Small Island Development States)	Sustainable human development	Education, environment, economy and health	Proposed a sustainability index similar to the HDI, based on the multiplicative approach of Zhou et al. [98]
Ogneva-Himmelberger et al. [72]	Studied the impact of environmental factors on the quality of life for residents of the American state of Massachusetts	Quality of life	Economy, demographics, poverty, housing, education and environment	Use of the DEA-PCA for construction of an index, which was compared with other techniques. Evaluated the impact of environmental variables in this index
Morais et al. [70]	Evaluated the quality of life of 246 European cities from the perspective of human capital	Quality of life	Social life, health, climatic conditions, economy, housing, leisure and transportation	Analyzed the quality of life from a particular stakeholder: the ability to attract skilled labor

Table 13 (*continued*)

Research	Description	Social term	Social dimensions	Contributions
Reig-Martínez [79]	Developed a method for comparing human development in European and the MENA countries	Human development	Economy, inequality, education, health and environment	Used, in three stages of the SBM model, clustering and a model of common weights
Martín and Mendoza [66]	Used the DEA to construct an index of quality of life of Municipalities of the Canary Islands	Quality of life	Economy, health, housing, education, security, leisure, social life, work and environment	Use of cross-evaluation to measure the weight of each variable
Mariano and Rebelatto [63]	Evaluated the efficiency of countries in converting economic wealth in quality of life	Quality of life	Health, education, economy, housing, cost of living, inequality, work and security	Use of weight restrictions and triple index to evaluate the social efficiency of countries
Debnath and Shankar [25]	Analyzed the efficiency of countries to convert good governance in happiness	Happiness	Happiness	Focus on the issue of happiness. Conducted a preliminary clustering to ensure homogeneous DMUs
Põldaru and Roots [73]	Measured the efficiency of 15 cities in Estonia in providing quality of life	Quality of life	Economy, health, environment and education	Integration of the DEA-SBM with PCA
Carboni and Russu [12]	Evaluated the well-being of 20 Italian regions between 2005 and 2011	Well-being	Health, economy, environment, education, social protection, work, leisure, inequality and social life	Used the ANN self-organization map to cluster the Italian regions and also used Malmquist index
Santana et al. [81]	Evaluated the efficiency of BRICS countries in generating sustainability	Sustainable development	Health, economy and environment	Carried out a separate analysis of efficiency for each of the three pillars of sustainability. Pioneers in studying the BRICS
Wu et al. [95]	Evaluated the efficiency of 19 OECD countries in generating HDI through capital and labor	Human development	HDI – economy, health and education	Compared the rankings of the efficiency and HDI
Guardiola and Picazo-Tadeo [42]	Analyzed the life satisfaction of 178 people in a province in Mexico	Life satisfaction	Health, economy, work, leisure, environment, social life and happiness	Concluded that DEA-MCDM do not improve the relationship with self-reported life satisfaction in comparison to the equally weighted index
Mizobuchi [68]	Built four different social indices from 11 social indicators for 34 OECD countries	Better life	Health, economy, work, housing, social life, environment, leisure, happiness and security	Compared indicators constructed with and without the incorporation of inputs

the studies assessed. Further details about the dimensions used in each study can be found in the Appendix.

Based on the data presented in the Appendix, it can be perceived that 16 of the 57 papers analyzed (28.07%) used only the three dimensions of the HDI: economic, education and health. This result is expected, given that the HDI is the main reference in terms of studies about human development. Table 11 shows the most explored dimensions on human development and DEA in the literature.

As showed in Table 11, it was possible to notice that, despite the substantial use of health and education dimensions, the most used dimension was the economic one, which covers aspects such as income, employment and economic growth. This fact indicates that there are few studies that can clearly separate the ‘ means’, which according to the approach of Sen [82], correspond to the economic aspects, from the ‘ end purposes’, which cover the purely social aspects. Interestingly, the HDI makes no such distinction, jointly covering economic (income per capita) and social aspects (education and life expectancy).

It is important to note that the environment dimension emerged compellingly (35.09%) as a new value observed in studies of human development, which ultimately integrates the social analyses into the broader sustainability aspect. Much more recently, there are some studies that must be highlighted as they address more subjective aspects related to leisure, social life and happiness. Despite the difficulty of measuring these aspects, the DEA can be an excellent tool for building indices related to these dimensions, which is the penultimate gap identified in this study:

G_{19} : Using the DEA to construct indices, or to evaluate efficiency, related to subjective well-being.

Finally, Table 12 presents an analysis of the number of variables that was used in each study, broken down into inputs and outputs. It should be noted that 69 analyses were considered, since more than one analyses were realized in nine articles: (a) Santana et al. [81]; (b) Mizobuchi et al. [68]; (c) Morais and Camanho [69]; (d) Friebelová and Friebel [36]; (e) Lefebvre et al. [54]; (f) Hatefi and Torabi [48]; (g) Malul et al. [62]; and (h and i) Despotis [27,29].

Table 12 shows that most of the analyses conducted use only of three or four input and output variables, which leads to the last gap broached in this study.

G_{20} : There is a lack of analyses that consider a large number of dimensions and variables.

As quality of life is a multidimensional definition, and since it is still far from any consensus on how to measure it, there is still much room for analyses using a higher number of variables. These analyses, however, depend on greater efforts by the measurement institutes, in addition to more advanced tools to assess aspects such as subjective well-being. Additionally, we must be careful not to use an excessive number of variables, especially if they represent a high degree of correlation, since besides impairing the discrimination power of DEA, it will not add any relevant information to the analysis.

5. Conclusions

The data envelopment analysis can be an excellent tool to help in the measurement and analysis of issues related to human development, and through it indexes with lower arbitrary weights can be composed, in addition to evaluating the efficiency in generating quality of life from wealth or economic, social and environmental resources.

This research considered a range of 57 articles published in the last two decades, and with them, it is believed, the state of the art on the subject could be properly mapped. This mapping considered the different analysis dimensions, including bibliometrics, scope, the DEA models and extensions used, the interfaces with other techniques, the units analyzed and the depth of the study. We believe that these analysis dimensions may be of use for other studies that propose to build the state of the art on a theme.

We highlight that only articles containing keywords related to the concept of human development were assessed, leaving out several studies which focused only on economic growth, such as Knox Lovell et al. [51], and others that have used sustainable development, which generally give more emphasis to environmental factors, as for instance citing the recent work of Rosano-Peña et al. [80].

As it can be seen in the last section, the economic and environmental dimensions have an important role in the analysis of quality of life, which proves that all these concepts still need a more precise definition.

Characterizations were developed in each analysis dimension, which enabled classifying all the articles found into categories. We hope that these categories give way to advances in the theoretical understanding of the subject and guide future works on the subject in order to locate them more appropriately in relation to the previous literature.

We understand, however, that the greatest advance of this work regards the 20 gaps assessed on the subject, which are distributed throughout the text. Each of these gaps can be considered an indicator for future research on the subject, as the gaps refer to both mathematical aspects of improvements in the techniques, as well as the measurement and standardization aspects of the terms used.

Appendix

Table 13 is a summary of each of the 57 papers analyzed in this work, which presents: (a) a brief description of the work; (b) the social term that was used; (c) the social dimensions analyzed; and (d) the main contributions of each work. Note that the articles were ordered by year of publication with the purpose of offering an evolutionary view of the research conducted in the area.

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