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Optimizing data-driven weights in multidimensional indexes

Lidia Ceriani [a], Chiara Gigliarano [b], Paolo Verme [c],*

[a] University of Bologna, Department of Political and Social Sciences, Italy
[b] LIUC University, School of Economics and Management, Italy
[c] University of Bologna, Department of Statistical Sciences, Italy

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ABSTRACT

Multidimensional indexes are ubiquitous, and popular, but present non negligible normative choices when it comes to attributing weights to their dimensions. This paper provides a more rigorous approach to the choice of weights by defining a set of desirable properties that weighting models should meet. It shows that Bayesian Networks is the only model across statistical, econometric, and machine learning computational models that meets these properties. An example with EU-SILC data illustrates this new approach highlighting its potential for policies.

1. Introduction

Social sciences, including economics and statistics, have recognized the importance of summary and synthetic measures that go beyond the representation of single variables or dimensions. Multidimensional indexes offer the opportunity to represent complex concepts such as well-being, happiness, or social capital with summary indicators. Examples of multidimensional indicators are Amartya Sen's indexes of well-being (Sen, 1980, 1985), the United Nations' Human Development Indexes, and the OECD's Better Life Index (OECD, 2015).

Despite their popularity, there is no consensus on how to aggregate dimensions and how weights should be attributed to each dimension. This has driven some organizations to adopt a "dashboard" approach where dimensions are monitored simultaneously, but separately. Examples of this approach are the OECD's Better Life Index (OECD, 2015), the Italian Equitable and Sustainable Well-being index (CNEL and ISTAT, 2015), and the United Kingdom's National Well-being Measure (Office for National Statistics, 2015). This approach highlights changes over time in each dimension, avoiding loss of information, but falls short of a parsimonious representation of well-being.

A more popular approach is to use a single composite weighted index. Examples are the Human Development Index (HDI), the Canadian Index of well-being (Canadian Index of Wellbeing, 2012), the Happy Planet Index (Foundation, 2013), and various multi-dimensional poverty or inequality indices used extensively by economists and statisticians (Alkire and Foster, 2011; Aaberge and Brandolini, 2015; Bosmans et al., 2015). The main drawbacks of this approach are the loss of information due to the extreme synthesis, and the arbitrariness of the choice of weights (particularly when weights are purely normative such as those based on researchers' or surveys respondents' opinions), and aggregation methods (OECD, 2008; Decancq and Lugo, 2013; Nguyen and Gigliarano, 2025/03/18; Belhadj, 2012).

An additional shortcoming of multidimensional analyses shared by the dashboard and index methods is that dimensions are assumed to be independent (orthogonal). This is a rather unrealistic assumption as eloquently argued by the Fitoussi commission when discussing the quality of life index (Stiglitz et al., 2010): "*it is critical to address questions about how developments in one domain of quality of life affect other domains*" (p.59) and "*when designing policies in specific fields, impacts on indicators pertaining to different quality-of-life dimensions should be considered jointly, to address the interactions between dimensions*" (p.16). These statements highlight the importance of the complex correlation structure among dimensions and also the relevance of the direction of association between dimensions and the overall structure of causality.

This paper addresses these questions by arguing that data-driven weights in multidimensional indexes should be derived from models that meet a set of desirable properties designed to address the questions of orthogonality of dimensions, loss of information, and causality. After specifying these properties, the paper reviews statistical, econometric, and machine learning models to assess which model meets these properties. It finds that Bayesian Networks is the only model that satisfies all the desirable properties identified. An example shows how this model offers a practical approach to weighting and policy making with multidimensional indexes.

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* Corresponding author.
E-mail addresses: lidia.ceriani@unibo.it (L. Ceriani), cgigliarano@liuc.it (C. Gigliarano), paolo.verme@unibo.it (P. Verme).

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2. A positive data-driven approach to weighting

When treating multidimensional concepts, scholars are faced with stark choices: ignoring the question of weights and monitor contributing dimensions separately (the “dashboard” approach), attribute equal weights, attribute different weights to different dimensions based on some normative criteria, or attribute weights based on some positive data-driven criteria. If one is searching for a single index with no priors on the importance of dimensions, the latter approach is understandably preferable, but there is no consensus on how to identify the optimal weighting model. In fact, there is hardly any discussion in the literature on what properties these data-driven models should meet.

A possible and more rigorous approach is to state first the properties that models designed to study associations across variables should meet to be used for weighting dimensions in multidimensional indexes. Based on the conclusions of the Fitoussi commission, the shortcomings identified in the literature, and the existing features of popular models used in statistics, econometrics and machine learning, we argue that a plausible data-driven weighting model should meet the following criteria: (1) Measure the correlation between the outcome variable of interest and each of the dimensions included into the index; (2) Measure the correlation across the dimensions that constitutes the index; and (3) Identify the direction of correlation among all variables. These are baseline properties that emerge from the literature discussed and can be regarded as essential to generate model-driven weights.

We add that other desirable properties are (4) Being able to identify an outcome variable when this variable is not easily identified. This property is added to expand the range of data settings that can be used for generating data-driven weights; (5) Be based on probabilistic rather than deterministic criteria. This allows to reduce the set of normative choices needed for identifying the set of relevant variables and their respective weights; and (6) Be suitable for deriving relative weights from estimated coefficients. That is because one needs to estimate the full set of multivariate correlations across dependent and independent variables. A model that satisfies these six criteria, we argue, addresses the combination of issues that plague weighting in data-driven multidimensional indexes.

The range of potential weighting models to consider is vast. In an effort to simplifying the analysis, and considering that multidimensional indexes typically provide a snapshot of the outcome considered, we excluded time models such as Granger, Markov, Panel, or Dynamic Bayesian Networks.[1] Otherwise, any model that studies cross-section associations among two or more variables can be considered a potential data-driven weighting model. It is important therefore to identify first a comprehensive list of models used across the social sciences to study association across variables, a rather ambitious task.

To address this question, we sought the help of ChatGPT and Deepseek. We first compiled a list of popular models used to study association across sets of variables such as Spearman, OLS, Logit, Principal Component Analysis, Random Forest, and others. This initial list was forcibly limited by the authors’ collective knowledge. We then asked both GPTs to complement this list with other popular models used across the social sciences. Next, we compared and assessed the lists provided, redacted a single list and submitted the list back to GPTs until authors and GPTs reached a consensus on a final list. We followed the same strategy to assess which model met which property by redacting an initial classification and ask both GPTs to comment until authors and GPTs reached an agreement on a final classification.

Fig. 1 summarizes results keeping models that met at least one of the desirable properties. The chart reports the number of properties that each model meets sorted in descending order. It shows that Bayesian Networks is the only model that satisfies all the six properties identified. Other models such as Structural Equation Modelling, Causal Forest and Neural Networks come close with five out of six properties satisfied whereas there are models that do not meet any property (not shown in chart), and others that meet only few. Also notable is the fact that some of the models that study associations well are not very suitable for constructing weights. Table A.1 in Annex qualifies the findings and groups models into categories (Correlation, Regression, Machine Learning, Graphical Networks, Dimensionality Reduction, Latent Variable, Weighting, Diagnostic).[2] As shown by the Table, some of the findings may be disputable as several models meet some of the properties only under certain specifications. However, Bayesian Networks is the only model that consistently showed to satisfy all the desirable properties identified. Even if we removed the probabilistic condition, which understandably reduces the range of models that can be considered, Bayesian Networks would still sit on top of the classification. The only other model that can potentially meet all six conditions is the Structural Equation Model. However, SEM can be used for causal inference only under strict assumptions, and is computationally very challenging as compared to BNs.

3. A Bayesian networks example

3.1. Data

We provide an example of multidimensional index using an index of well-being based on the 2013 wave of EU-SILC, the European Union Statistics on Income and Living Conditions. We consider *life satisfaction* as our target (outcome) variable and include most of the key well-being dimensions suggested by the literature for these types of indexes including: *material living standards*, (ii) *health*, (iii) *education*; (iv) *personal activities and work*, (v) *political voice and governance*, (vi) *social connections and relationships*, (vii) *security of physical as well as economic nature*, (iix) *environment*, and also *age*, *gender* and *country* as control variables. The unit of analysis is the household head. We include in the analysis all countries belonging to the European Union, with the exception of Czech Republic, Denmark and Slovenia, because they lack information on one of the dimensions of social connections and relationships (variable pd050) (See Liberati et al., 2023 and Bossert et al., 2013 for papers that use EU-SILC data for multidimensional indexes of well-being. See also Ceriani and Gigliarano, 2020 for a first application of Bayesian Networks to weighting in multidimensional indexes of well-being).

3.2. A Bayesian network of dimensions

We estimate a set of Bayesian Networks’ structures using eleven different algorithms, including constraint-based learning algorithms, scored-based learning algorithms, and hybrid algorithms (we use the R package *bnlearn* conceived by Scutari, 2010). We have also forced a set of arcs not to be included in the graph, by means of a blacklist, in order to avoid the control variables age and household size to be considered dependent of the well-being dimensions. Also, we have excluded the directed arcs from status in employment (WORK) and poverty (M_POOR) to education (EDU) and from satisfaction with life (SA_LIFE) to health (HEALTH). Moreover, we have whitelisted the directed arc from EDU to WORK, as our prior is that level of education should affect status in employment.

Table 1 reports the arcs’ occurrence in each of the BN obtained by implementing the 11 algorithms. Following Cugnata et al. (2016), we assign a weight of 1 to arcs linking pairs of nodes directly and a weight

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[1] Note that longitudinal studies with multidimensional indexes exist (see for example Zhang et al., 2021) but are few.

[2] Note that several models would fit different groups. This is a coarse classification that is useful to see how classes of models behave. It is also useful to compare a reduced set of models that are representative of the main classes as shown further in the paper.

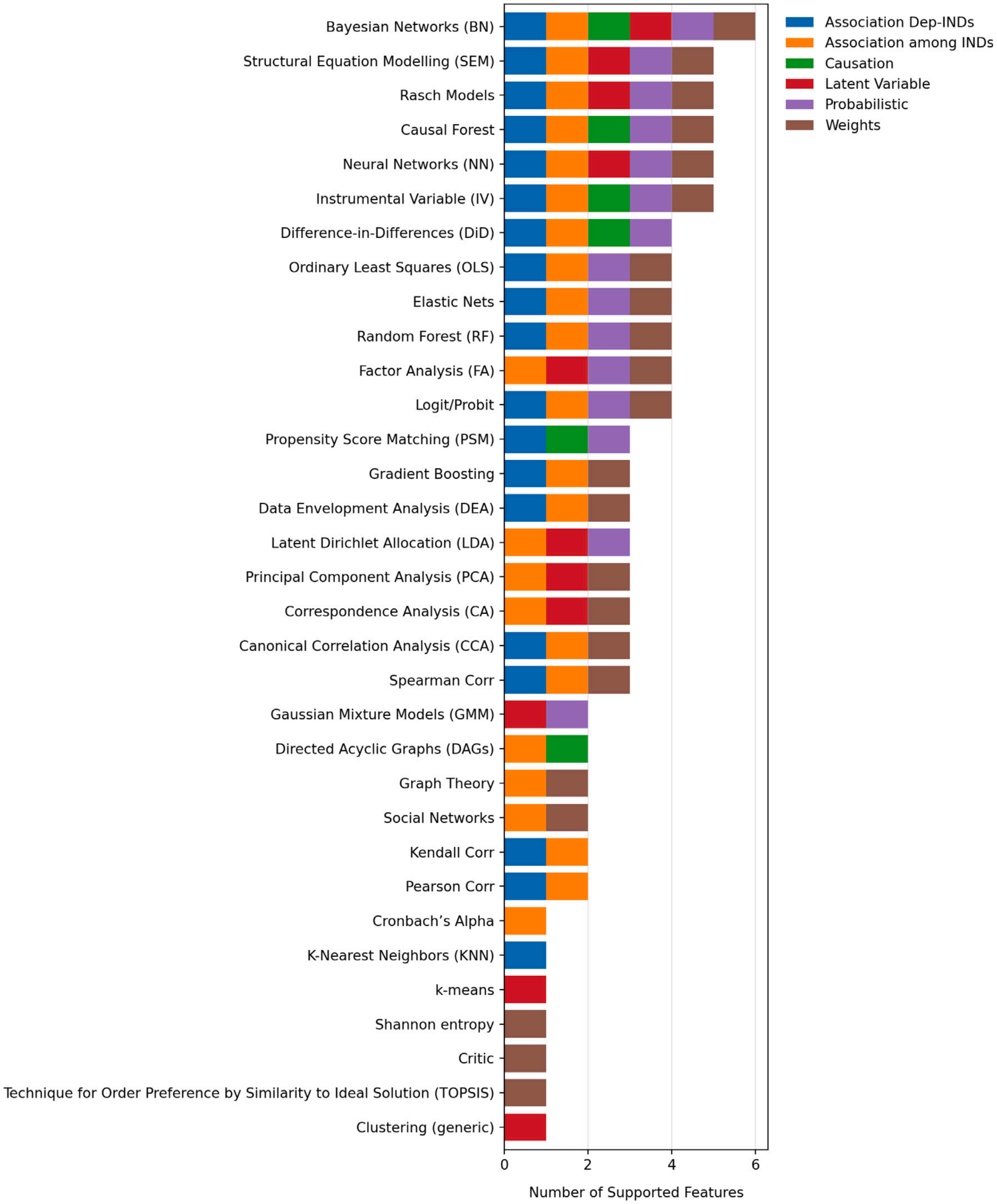

Fig. 1. Comparing potential weighting models.

of 0.5 if the connection is indirect. The last column in each table shows the sum of weights assigned to each pair of nodes, which can vary between 0 and 11. For the purpose of this paper, we define robust a BN which contains the largest set of arcs scoring 6 or more, meaning that the majority of algorithms find an occurrence.

The network resulting from applying the Tabu-aic algorithm in Fig. 2 contains the highest number of arcs among all networks produced by the 11 different algorithms applied. The numbers shown on the arcs represent the number of algorithms confirming the directional connections. See, for example, age to EDU and EDU to WORK, which correspond to the first two rows of Table 1. The arcs that appear in at least 6 of the 11 algorithms used in the analysis are depicted in red. Variables of interest (non-control variables) are in capital letters. The numbers on the arcs represent the number of algorithms confirming the directional connection. In red the arcs contained in more than 5 algorithms.

Of the different well-being dimensions taken into account, only education (EDU), personal activities and work (WORK), material living standards (M_MD and M_POOR), economic security (S_ECON) and health status (HEALTH) influence the target variable (satisfaction with

Table 1

List of arcs from different learning algorithms.

Arcs		Score-based					Constraint-based				Hybrid		TOT
		HC			TABU		GS	INCAS			MMHC		
		bic	aic	k2	bic	aic			fast	int	bic	rm	
age	EDU	1	1	1	1	1	1	1	1	1	1	1	11
EDU	WORK	1	1	1	1	1	1	1	1	1	1	1	11
HEALTH	SA_LIFE	1	1	1	1	1	0	1	0	1	1	1	9
gender	S_ECON	0	1	1	0	1	1	1	1	1	1	1	9
age	HEALTH	1	1	1	1	1	0	1	0	1	1	0	8
country	WORK	1	1	1	1	1	1	0	0	1	0	1	8
country	SA_LIFE	0	1	1	0	1	1	1	1	1	1	0	8
M_MD	SA_LIFE	1	1	1	1	1	0	1	0	1	0	0	7
country	gender	1	1	1	1	1	0.5	0.5	0.5	0	0	0	6.5
NATURE	S_PHYS	1	1	1	1	1	0	0	0.5	0	1	0	6.5
country	M_MD	1	1	1	1	1	0	0	0	1	0	0	6
SA_LIFE	NATURE	1	1	1	1	1	0	0	0	0	1	0	6
country	NATURE	1	1	1	1	1	0	0	0	0	0	0	5
country	POL	1	1	1	1	1	0	0	0	0	0	0	5
country	S_ECON	1	1	1	1	1	0	0	0	0	0	0	5
country	S_PHYS	1	1	1	1	1	0	0	0	0	0	0	5
M_MD	S_ECON	1	1	1	1	1	0	0	0	0	0	0	5
M_MD	SOC	1	1	1	1	1	0	0	0	0	0	0	5
SA_LIFE	POL	1	1	1	1	1	0	0	0	0	0	0	5
SA_LIFE	SOC	1	1	1	1	1	0	0	0	0	0	0	5
country	EDU	0	1	1	0	1	0	1	0	1	0	0	5
M_MD	M_POOR	1	1	0	1	1	0	0	0	0	0	0	4
S_ECON	HEALTH	1	1	0	1	1	0	0	0	0	0	0	4
country	M_POOR	0	1	1	0	1	1	0	0	0	0	0	4
POL	NATURE	0	1	0	0	1	0	1	0	1	0	0	4
S_PHYS	NATURE	0	0	0	0	0	0	1	0.5	1	0	1	3.5
…	…	..	..	..	..	..	..	..	..	..	..	..	..

Note: Arcs supported by less than 3 algorithms are not reported.

life, SA_LIFE). On the other hand, political and social participation (SOC and POL), satisfaction with the environment (NATURE) and physical security (S_PHYS) appear to be consequences of the level of life satisfaction (SA_LIFE). These findings are sensible but recall that researchers may whitelist or blacklist variables based on prior knowledge or common sense. In other words, researchers can impose as much structure as they like on the BN following the initial data-driven analysis.

3.3. *Generating weights from Bayesian networks*

The information on the strength of the relationship between nodes can be naturally translated in the weighting structure of a multidimensional index of well-being. In this new system of weights, dimensions that have a larger impact on the target node when affected by a policy-induced change (e.g. have *more influence* on the target node) receive a higher weight.

Let us assume that T is the target node (*satisfaction with life*). For each i−th dimension of well-being, the weight assigned to dimension X_i is positively correlated with the strength of the arcs connecting X_i and T and negatively correlated to the length of the path linking X_i with T. Formally:

$$w_i(X_i, T; p_i) = \sum_{p_i \in P_i(X_i,T)} \sigma_i^{|p_i|} \tag{1}$$

where $P_i(X_i, T)$ is the set of paths in the BN joining nodes X_i and T, $|p_i|$ is the length of each path and σ_i is the strength associated to each path. A path is defined as the set of arcs connecting each node X_i to the target node T. The strength of each path corresponds to the product of the strengths of each arc in the path (which are bounded between 0–no influence between two nodes and 1–maximum influence). This definition of weight corresponds to the *distance-weighted influence* in Albrecht et al. (2014) and Cugnata et al. (2016).

The proposed definition of weights represents an improvement on the classical *data-driven* and *normative* approaches to weights found in the literature (see Decancq and Lugo, 2013 for a discussion). As for *data-driven* weights, BN weights consider the distribution of achievements in society and, as in the *normative* approach, they attribute more weight to policy relevant variables. Unlike these approaches, BN weights include data-driven information on inter-dependencies among variables and can be used for *ex-ante* prognostic (forecasting) and *ex-post* diagnostic (evaluation) policy purposes. By providing this extra information, they also partly address the criticism of loss of information attributed to the multidimensional index approach.

4. Comparing different weighting schemes

As a further illustration, we compare the resulting rankings of selected weighting schemes representing the main classes of models including: (i) Spearman Correlation; (ii) Linear Regression; (iii) Random Forest; and (iv) Bayesian network. As benchmarks, we also use (v) Equal Weighting; and (vi) Self-reported opinions from Eurobarometer. Such comparison is parsimonious enough to allow for a visual assessment while comparing different classes of weighting schemes.

As multivariate correlation-based method, we use the Spearman rank correlation coefficient, which seems the most appropriate given the categorical nature of our underlying data (see Banerjee, 2018 for a discussion on deriving multidimensional weights using multidimensional coefficient of variation). Each dimension weight is defined as the absolute value of the correlations coefficient (ρ) between the dimension and the target variable t, plus half the value of each other pairwise ρ's:

$$w_i^{SC} = \|\rho_{i,t}\| + \frac{1}{2} \sum_{j \neq i,t} \|\rho_{i,j}\|$$

Weights are then normalized dividing by $\sum_{i \neq t} w_i$. Notably, this method offers an improvement over linear estimation by capturing pairwise correlations among independent variables; however, it remains limited in its ability to reveal the broader network of interrelationships across dimensions.

As machine learning method, we apply Random Forest regression algorithms, and we use as weights the predicted importance associated to

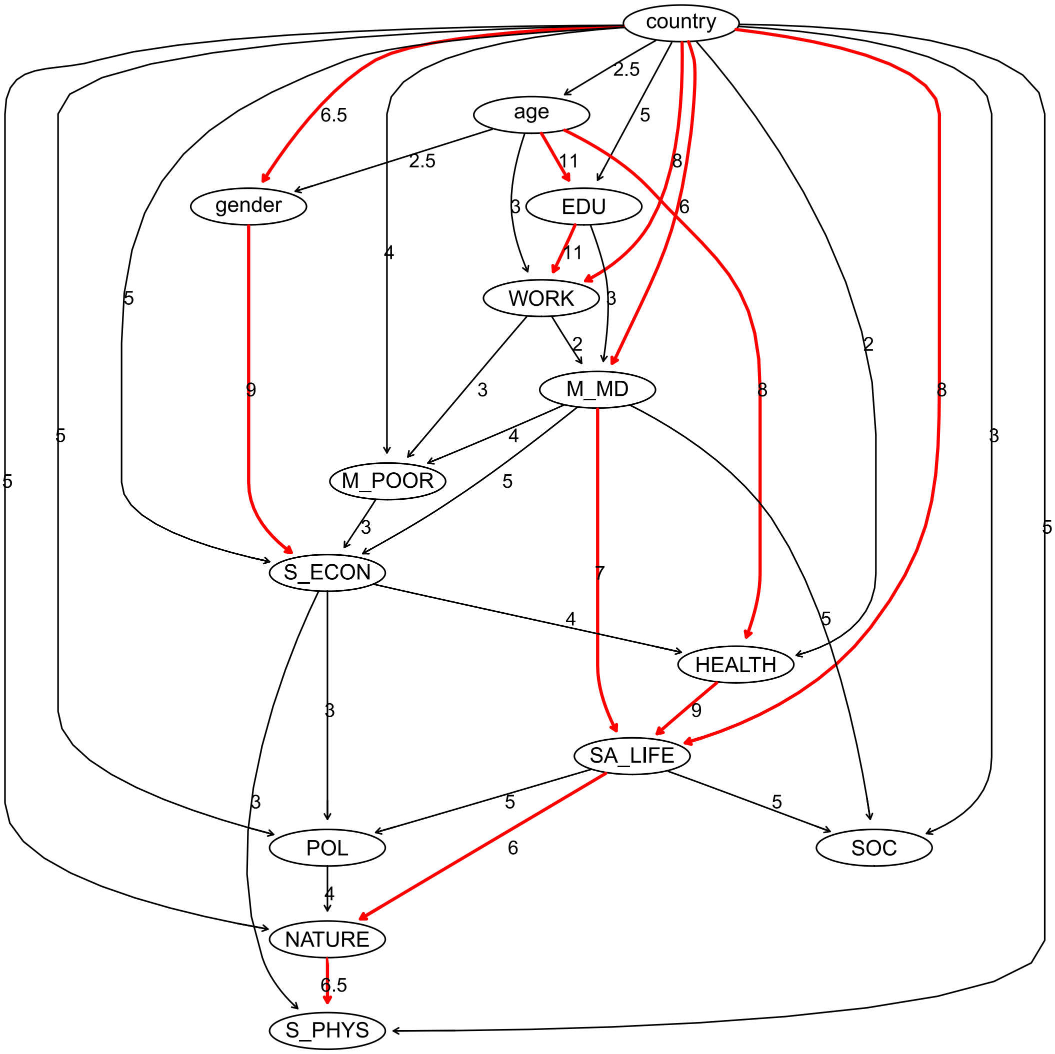

Fig. 2. Robust BN (Tabu-aic algorithm).

each independent variable, ι_i, normalized by the sum of all importance values associated to each dimension i–th, $i = 1, \ldots, m$:

$$w_i^{RF} = \frac{\iota_i}{\sum_{i=1}^{m} \iota_i}$$

For the opinion-based weights, we use data from the Eurobarometer survey, wave 86.3 fielded between November and December 2016. The weight are represented by the share of the population expressing strong concern with respect to selected issues, following Guio et al. (2009) and Bossert et al. (2013). Table 2 summarizes the variables used to capture the relative importance that individuals attach to each dimension.

The application of multiple weighting methods reveals substantial variation in how well-being dimensions are prioritized (see Table 2). From a policy perspective, the equal weighting approach offers limited analytically utility, as it fails to account for the varying influence of each dimension. Subjective weights highlight Satisfaction with One's Economic Situation, Social Participation, Health, and Satisfaction with Work as the most salient contributors to overall life satisfaction, reflecting individual or cultural perceptions of well-being. In contrast, data-driven methods such as OLS regression, Random Forest, and Spearman correlation produce more balanced distributions, yet consistently assign greater importance to Health, Material Deprivation, and Economic Satisfaction. Among these, Random Forest produces a particularly even distribution of weights, assigning relatively lower importance to Poverty Status, Economic Satisfaction, and Physical Security, while giving slightly more weight to Material Deprivation, Environmental Satisfaction, and Satisfaction with Work.

Table 2
Weights (in %) assigned to wellbeing dimensions using different methods.

Dimension	EQ	EB	RE	SP	RF	BN
Education (EDU)	10	6.6	.7	10	9.6	0
Health (HEALTH)	10	11.2	21.5	10.4	11	46.9
Material Deprivation (M_MD)	10	9.9	12.8	11.6	15.9	52.7
Being Poor (M_POOR)	10	8.8	9.5	8.1	6.9	0
Satisfaction with Nature (NATURE)	10	6.8	10.6	11.7	9.7	0
Political Participation (POL)	10	7.5	11.7	10.4	10.2	0
Social Participation (SOC)	10	12.3	16.8	10.5	10.9	0
Economic Security (S_ECON)	10	21.1	12.6	8.6	13.2	.4
Physical Security (S_PHYS)	10	4.1	2.4	8.1	3	0
Work Satisfaction (WORK)	10	11.9	1.4	10.6	9.7	0

Bayesian Networks (BN), Subjective Weights (EB), Equal Weights (EQ), OLS Regression (RE), Random Forest (RF), and Spearman Correlation (SP).

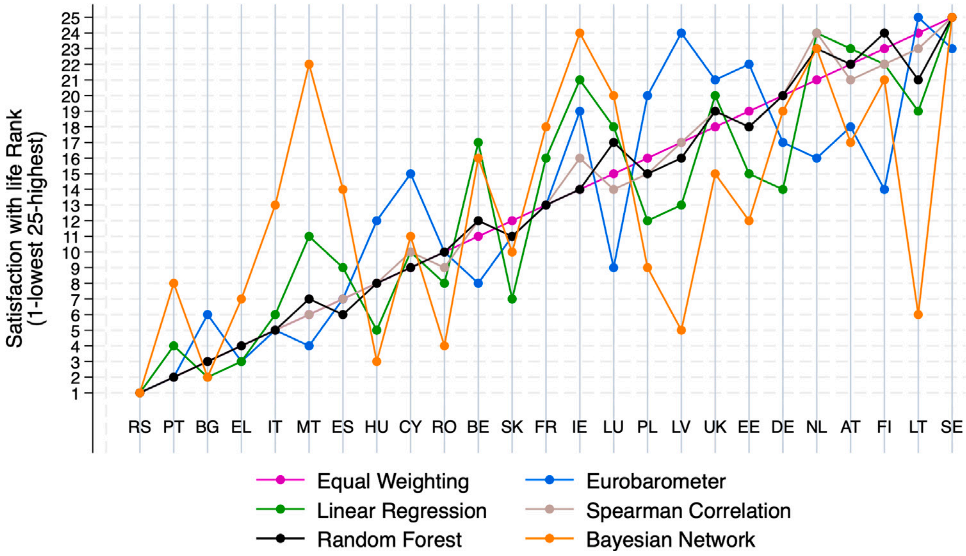

Fig. 3. Ranking of countries according to different weighting scheme.
Source: Authors' calculations.

Bayesian Networks, on the other hand, allocate nearly all the weight to Health and Material Deprivation. This concentration reflects the model's ability to account for both direct and indirect effects, revealing that these two dimensions exert the greatest overall influence on life satisfaction. Their centrality arises not only from their direct impact but also from their role in shaping other dimensions within the well-being framework. This capacity to capture indirect pathways is a key advantage of the Bayesian Network approach over alternative methods. Specifically, it offers three critical benefits: (i) it incorporates indirect effects, providing a more comprehensive understanding of causal influence; (ii) it narrows the range of policy actions required to improve outcomes; and (iii) it enhances the cost-effectiveness of interventions by leveraging the amplifying potential of indirect relationships.

Fig. 3 clearly demonstrates that the choice of weighting method is not neutral: it can significantly shift a country's rank in a composite well-being index. While data-driven methods tend to offer more consistent patterns, subjective or structure-based approaches (like Eurobarometer and Bayesian Networks) can produce markedly different outcomes, especially for countries in the middle of the distribution. In particular, the large changes observed in the ranks of Malta (MT), Latvia (LV), and Lithuania (LT) are due to the BN method placing almost all the weight on the HEALTH and M_MD dimensions. In these dimensions, LV and LT rank among the worst performers, while MT ranks among the best across all countries considered. Conversely, in the remaining dimensions, LV and LT are among the best performers, whereas MT ranks among the worst. With all other methods, the relative performance across all dimensions is smoothed out, resulting in more moderate changes in country rankings.

A key limitation of Bayesian networks (BNs) lies in their reliance on simplifying assumptions that may not hold with real-world data. Multivariate datasets rarely follow standard parametric distributions, such as multivariate Gaussian or Multinomial. Computing partial correlations – essential for structure learning – can be problematic due to matrix singularities, particularly in high-dimensional or sparse datasets. In mixed data scenarios, parametric models impose structural constraints, such as prohibiting continuous variables from being parents of discrete ones. A common workaround is to discretize continuous variables; however, this can lead to a significant loss of information and requires careful calibration to preserve meaningful dependencies. Similarly, treating ordinal variables as purely categorical further reduces the richness of the data, potentially weakening the model's accuracy and interpretability. Another important limitation of BNs is the assumption that all relevant variables are observed — meaning there are no latent or unmeasured variables influencing the system. In practice, however, many real-world datasets are affected by hidden confounders that can introduce spurious correlations among the observed variables. These variables can distort the true dependency structure: the network structure does not account for them, and an arc could be incorrectly added between two observed variables due to the unmodeled influence of a hidden one. As a result, the inferred causal graph may include misleading or artificial dependencies that do not reflect the true data-generating process (Scutari and Denis, 2014).

5. Conclusions

The paper showed that Bayesian Networks is the only model meeting a set of desirable properties identified for weighting in multidimensional indexes. This model offers a clear graphical representation of the hierarchical sets of relations across dimensions, it can be easily used to derive weights, and results in clearer, more parsimonious, and potential cost-efficient policy indications.

During the preparation of this work the authors used ChatGPT and Deepseek in order to prepare Fig. 1 and Table A.1. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix

See Table A.1.

Table A.1
Comparing potential weighting models.

	Group	Models	Association Dep-INDs	Association among INDs	Causation
1	Corr	Pearson	Yes	Yes (bivariate)	No
2	Corr	Spearman	Yes	Yes (bivariate)	No
3	Corr	Kendall	Yes	Yes (bivariate)	No
4	Corr	CCA	Yes	Yes (multivariate sets)	No
5	Reg	OLS	Yes	Yes (DV vs. IVs)	No (unless assumptions hold)
6	Reg	Logit/Probit	Yes	Yes (DV vs. IVs)	No (unless causal design)
7	Reg	IV	Yes	Yes (DV vs. IVs, accounting for endog.)	Yes (with valid IV)
8	Reg	DiD	Yes	Yes (causal DV-IV)	Yes (under parallel trends)
9	Reg	EN	Yes	Yes (DV vs. IVs)	No
10	Reg	SEM	Yes	Yes (network of DV-IV links)	Yes (if causal model specified)
11	Reg	PSM	Yes (causal)	No (balances groups, no direct assoc.)	Yes
12	ML	RF	Yes	Yes (implicit feature interactions)	No
13	ML	Causal Forest	Yes	Yes (causal DV-IV)	Yes (heterogeneous effects)
14	ML	Gradient Boosting	Yes	Yes (implicit feature interactions)	No
15	ML	NN	Yes	Yes (complex nonlinear assoc.)	No
16	ML	KNN	Yes (predictive)	No (instance-based, no formal assoc.)	No
17	ML	Clustering (generic)	No (unsupervised)	No (groups observations)	No
18	ML	k-means	No (unsupervised)	No (groups observations)	No
19	ML	GMM	No (unsupervised)	No (groups observations)	No
20	ML	LDA	No (topic modeling)	Yes (doc-word co-occurrence)	No
21	GN	BN	Yes (probabilistic)	Yes (conditional dependencies)	Yes (if causal structure known)
22	GN	DAGs	No (framework)	Yes (represents causal assoc.)	Yes (theoretical basis)
23	GN	Graph Theory	No (math framework)	Yes (abstract relational structure)	No
24	GN	Social Networks	No (relational analysis)	Yes (node-edge relationships)	No (unless causal design)
25	DR	PCA	No (dim. reduction)	Yes (covariance among variables)	No
26	DR	FA	No (latent structure)	Yes (latent variable assoc.)	No
27	LV	CA	No	Yes	No
28	LV	Rasch Models	Yes	Yes (item-person links)	No
29	WE	Shannon entropy	No (info theory)	No (measures uncertainty)	No
30	WE	Critic	No (weighting method)	No (objective weights)	No
31	WE	TOPSIS	No (MCDA method)	No (ranking alternatives)	No
32	WE	DEA	Yes (input–output)	Yes (efficiency frontiers)	No
33	DG	VIF	No (diagnostic tool)	No (measures multicollinearity)	No
34	DG	Cronbach's Alpha	No	Yes	No

(*continued on next page*)

Table A.1 (*continued*).

	Group	Models	Latent variable	Probabilistic	Weights	Reference
1	Corr	Pearson	No	No	No	OECD (2008)
2	Corr	Spearman	No	No	Yes (only for diagnostic)	Mazziotta and Pareto (2016)
3	Corr	Kendall	No	No	No	Not Found
4	Corr	CCA	No	No	Yes (canonical weights)	Härdle and Simar (2015)
5	Reg	OLS	No	Yes (with inference)	Yes (coefficients as weights)	Cherchye et al. (2007)
6	Reg	Logit/Probit	No	Yes	Yes (coefficients as weights)	Krishnakumar (2007)
7	Reg	IV	No	Yes	Yes (coefficients as weights)	Heckman and Vytlacil (2007)
8	Reg	DiD	No	Yes (with SEs)	No	Not Found
9	Reg	EN	No	No (unless Bayesian)	Yes (shrunk coefficients)	Greco et al. (2019)
10	Reg	SEM	Yes (common in SEM)	Yes	Yes (path coefficients)	Booysen (2002)
11	Reg	PSM	No	Yes (with uncertainty)	No	Not Found
12	ML	RF	No	No (unless Bayesian RF)	Yes (feature importance)	Berrar et al. (2016)
13	ML	Causal Forest	No	Yes	Yes (feature importance)	Athey and Imbens (2016)
14	ML	Gradient Boosting	No	No	Yes (feature importance)	Chen and Guestrin (2016)
15	ML	NN	Yes (context-dependent)	Yes (if Bayesian)	Yes (attention weights)	Kokotović and Dželihodžić (2020)
16	ML	KNN	No	No	No	Not Found
17	ML	Clustering (generic)	Yes (latent clusters)	No	No	OECD (2008)
18	ML	k-means	Yes (latent clusters)	No	No	Asselin (2009)
19	ML	GMM	Yes (latent distributions)	Yes	No	Bartholomew et al. (2008)
20	ML	LDA	Yes (latent topics)	Yes	No	Not Found
21	GN	BN	Yes (latent nodes possible)	Yes	Yes (conditional probabilities)	Delgado and Salini (2018)
22	GN	DAGs	No	No	No	Not Found
23	GN	Graph Theory	No	No	Yes	Cobo et al. (2011)
24	GN	Social Networks	No	No	Yes	Freeman (1979)
25	DR	PCA	Yes (latent components)	No	Yes (loadings as weights)	Jolliffe (2002)
26	DR	FA	Yes (primary purpose)	Yes	Yes (factor loadings)	OECD (2008)
27	LV	CA	Yes	No	Yes	Greenacre (1984)
28	LV	Rasch Models	Yes	Yes	Yes (item difficulty params)	Fusco and Dickens (2008)
29	WE	Shannon entropy	No	No	Yes	Zeleny (1982)
30	WE	Critic	No	No	Yes (explicit weighting method)	Diakoulaki et al. (1995)
31	WE	TOPSIS	No	No	Yes (explicit weighting method)	Hwang and Yoon (1981)
32	WE	DEA	No	No	Yes (custom DMU weights)	Cherchye et al. (2007)
33	DG	VIF	No	No	No	Not Found
34	DG	Cronbach's Alpha	No	No	No	OECD (2008)

Legenda: Corr = Correlation; Reg = Regression; ML = Machine Learning; BN = Bayesian Networks; GN = Graphical Networks; DR = Dimensionality reduction; LV = Latent Variable; WE = Weighting; DG = Diagnostic; Canonical Correlation Analysis (CCA), Ordinary Least Squares (OLS), Instrumental Variable (IV), Difference-in-Differences (DiD), Elastic Nets (EN), Structural Equation Modeling (SEM), Propensity Score Matching (PSM), Random Forest (RF), Neural Networks (NN), K-Nearest Neighbors (KNN), Gaussian Mixture Models (GMM), Latent Dirichlet Allocation (LDA), Bayesian Networks (BN), Directed Acyclic Graphs (DAGs), Principal Component Analysis (PCA), Factor Analysis (FA), Correspondence Analysis (CA), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Data Envelopment Analysis (DEA), and Variance Inflation Factor (VIF).

Data availability

Data are publicly available.

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