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Using HJ-Biplot and External Logistic Biplot as Machine Learning Methods for Corporate Social Responsibility Practices for Sustainable Development

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Abstract: In recent years, social responsibility has been revolutionizing sustainable development. After the development of new mathematical techniques, the improvement of computers' processing capacity and the greater availability of possible explanatory variables, the analysis of these topics is moving towards the use of different machine learning techniques. However, within the field of machine learning, the use of Biplot techniques is little known for these analyses. For this reason, in this paper we explore the performance of two of the most popular techniques in multivariate statistics: External Logistic Biplot and the HJ-Biplot, to analyse the data structure in social responsibility studies. The results obtained from the sample of companies representing the Fortune Global 500 list indicate that the most frequently reported indicators are related to the social aspects are labour practices and decent work and society. On the contrary, the disclosure of indicators is less frequently related to human rights and product responsibility. Additionally, we have identified the countries and sectors with the highest CSR in social matters. We discovered that both machine learning algorithms are extremely competitive and practical to apply in CSR since they are simple to implement and work well with relatively big datasets.

Keywords: machine learning; multivariate analysis; HJ-Biplot; external logistic biplot; corporate social responsibility (CSR); sustainable development

1. Introduction

In recent decades, there has been a notable increase in interest worldwide in relation to social impacts, which has caused direct influence on the management of corporate social responsibility (CSR) practices, mainly by large corporations [1–4]. CSR refers to a set of strategies and actions that companies promote in order to satisfy stakeholder expectations [5], in addition to attracting the attention of the scientific community [6–9]. In this context, companies have expanded their interest in supporting sustainable development initiatives, influencing the adoption and execution of activities with social responsibility (SR). The CSR method assists companies to balance the management of their actions in relation to the three dimensions of sustainability: economic, environmental, and social, allowing for more sustainable business behaviour [10–13].

Sustainability reports are an alternative for corporations to transparently publicize the management of corporate practices in order to highlight the commitment and contribution towards social and environmental impacts [14,15]. Voluntary and public disclosure of these activities strengthens companies' credibility and reputation, enhancing their competitive and value-added status [16–20]. Furthermore, the publishing of these documents allows companies to portray themselves as world leaders in the eyes of society.

When it comes to corporate sustainability, the global reference framework is the Global Reporting Initiative (GRI) [21]. The GRI is an independent international organisation and a pioneer in the presentation of sustainability reports from 1997 to the present. This organisation guides companies and governments worldwide to understand and communicate their impact on sustainability issues, specifically in matters of climate change, human rights, governance, and social welfare [22]. GRI standards are the most widely used worldwide for the preparation of sustainability reports. The structure of the GRI indicators is centred in principle on the three dimensions of the conventional concept of sustainability: economic, environmental and social [23]. Subsequently, they are organised into categories, aspects and indicators. In this study, we have used the GRI-G4 version, guidelines accepted and widely used by the main companies worldwide [24]. Some researchers agree that the size of organisations influences the disclosure of information about their business operations, being large corporations the most sustainable [15,25–33].

However, this is not the first time that the commitment in CSR that companies have worldwide has been studied from a multivariate perspective; Cubilla-Montilla et al. used the HJ-Biplot to predict the influence of cultural values as normative pressure on the disclosure of information by companies [34], Murillo-Avalos et al. analysed the differences and similarities of large and multinational companies in relation to the dissemination of environmental information through HJ-Biplot and ELB [35], and Amor-Esteban et al. with the application of the X-Statis and HJ-Biplot captured the influence of institutional forces in relation to the commitment to sustainability exercised by companies [36]. The Logistic Biplot has been frequently utilized in the literature on social problems in both micro- and macroeconomic contexts, ref. [37], for example, investigates the impact of social capital on regional waste recycling; reference [38] investigates the creation of an index for social sustainability based on a DALY weighting approach; recently, [34] analysed the social indicators that are reported less frequently by companies.

The scope of the proposed objectives was achieved with the use of the Biplot [39], a statistical technique whose graphic representation combines individuals (global companies) and variables (GRI social indicators). Specifically, we use the External Logistic Biplot [40] (ELB) and HJ-Biplot. Biplot methods are a low-dimensional graphic representation of a multivariate data matrix (individuals x variables). The first biplots proposed by [39] were the GH Biplot and the JK Biplot, which were the two most important biplot factorisations. The GH Biplot produces a high-quality depiction of the variables, whereas the JK Biplot produces a high-quality picture of individual ranks. An optimization of these methods was proposed by [41]; this contribution maximizes the representation quality of both rows and columns at the same time. The first technique utilized is ELB which identifies the presence or absence of indicators of the social dimension in each of the selected companies. The second technique applied is the HJ-Biplot [41] to evaluate the similarities between the countries that serve the companies in the study, since, unlike other techniques, it makes it easier to visually detect the behaviour of geographic areas with respect to various dimensions (GRI social indicators) [42], in addition to achieving the highest quality of representation for rows and columns in the same reference system [43].

The multivariate statistical techniques that we have used are two-dimensional reductions applied to machine learning. Machine learning (ML) is the study of computer algorithms that learn on their own [44]. It is thought to be a subset of artificial intelligence [45]. Machine learning algorithms construct a mathematical model using sample data, referred to as "training data" in order to make predictions or choices without being explicitly programmed to do so [46]. In the academic literature, machine learning (ML) approaches have been offered as alternatives to statistical approaches for predicting companies' behaviour in the context of sustainable develop. ML has grown in popularity over the last decade, thanks to a slew of high-profile applications in autonomous vehicles, picture and speech recognition, automatic translations, the medical field, predicting COVID-19 and in the process engineering field [47–49]. There are some techniques that use this type of binary data; however, none provide a simultaneous representation of rows and columns [50].

This study specifies which social indicators are reported more frequently by companies in the FORTUNE Global 500 Ranking and which are managed less frequently. Additionally, CSR level profiles were established based on the similar or different behaviours of companies at the country level. The results of this study can provide a comprehensive scientific method to guide companies worldwide in identifying problems in their organizational system in relation to CSR practices, contributing to decision-making to improve their sustainable behaviour.

Our work proposes a double objective. First, we propose the analysis of mathematical techniques: External Logistic Biplot and HJ-Biplot, for the analysis of the structure of the data in social studies of sustainability. Second, we evaluate the commitment to CSR that the world's largest companies have by inspecting the indicators of the social dimension more and less reported to the GRI with these multivariate Machine Learning techniques.

The article is organised in the following manner. First, we provide a brief description of the GRI index and the Fortune Global 500. The second section describes the sample, the measurement of the variables, and the multivariate methods applied. The third section presents the results of the case study and then they are discussed in the fourth section. The conclusions are specified in the final section.

2. Materials and Methods

2.1. Population and Sample

In this study, the target population was the ranking of the largest companies in the world in 2017 (measured by their income), according to the Fortune Global 500. The selection for the sample was limited to companies that reported sustainability reports in 2017, according to the GRI-G4 guidelines. In this sense, the final sample corresponds to 158 companies that disclosed information on the performance of their corporate social responsibility practices through a sustainability report. The decision of the case study was made given the unique characteristics of the selected companies. Specifically, information about their business behaviour is more exposed to stakeholders, and in turn, they are considered the most active in sustainability [51].

2.2. Variables for Analysis: Social Indicators

We have worked with the 48 performance indicators that correspond to the social dimension of the Global Reporting Initiative in its fourth version. The GRI has organised these social indicators into 4 sub-categories: labour practices and decent work, human rights, society and product responsibility. Appendix A shows the GRI-G4 social indicators in detail.

2.3. Analysis Techniques

The information can come in different forms; some data can be categorical, nominal, and quantitative. Within these classifications we find the binary data. The data used in our study was structured in a binary $I \times J$ data matrix $\mathbf{A}_{I\times S}$ in which the rows (I) correspond to the 158 largest corporations in the world, and the columns (J) correspond to the 48 social indicators. Social indicators are binary variables that take the value of one when it is present and zero when it is not.

The ordination and design of the data imply the use of bidirectional techniques that allow graphical representations with clear statistical support to encourage the visual analysis of the findings, also providing an adequate understanding such as the prediction of their evolution. Based on matrix one, two more matrices were elaborated. The first one focuses on the percentage of disclosure of the most representative indicators at the country level, and the second summarises the disclosure of social information in percentage by sector.

The two multivariate techniques that were applied for the analyses were the External Logistic Biplot and HJ-Biplot. The software used to carry out these analyses was MULTBIPLOT, developed by [52], available on the website: http://biplot.usal.es/multbiplot (accessed on 21 July 2021) and the MultbiplotR in *R* [53], available on the website: https://CRAN.R-project.org/package=MultBiplotR (accessed on 21 July 2021). This program was written in R language [54].

3. External Logistic Biplot (ELB)

As a technique of ordination, the algorithm begins with a Principal Coordinates Analysis (PCoA). PCoA is concerned with the challenge of building a configuration of n points in a Euclidean space, representing the companies such that the distance between any two of these points approximates the dissimilarity between the companies as close as possible.

Let us suppose that we have an observed distance matrix $\Delta_{(I \times I)}$ obtained from a similarity coefficient calculated with the binary data matrix. The aim of PCoA is obtaining a configuration $\mathbf{A}_{I \times S} = (a_{is})$ in a lower-dimensional Euclidean space $\mathbb{R}^S$ whose interpoint distance matrix $\mathbf{D}$ is as close to as possible to Δ. We can find an exact configuration in $n-1$ dimensions when the observed dissimilarity/distance assessed is "Euclidean". Projecting onto the first k main coordinates or dimensions (typically $k = 2$) provides a lower-dimensional approximation or ordination diagram. The proportion of total variance explained by k dimensions (overall goodness of fit or overall quality of representation) may be calculated by taking the average of the n points in the graphical representation.

In contrast with Biplots, where the new axes may be understood in terms of the original variables, the axes in PCoA have no direct meaning. It is well known that PCA configurations may also be produced by applying PCoA to the Pythagorean distance matrix and that a classical biplot is obtained just by regressing the observed variables on the configuration.

An easy heuristic generalization for binary data is to use Logistic Regressions (LR) of each observed binary variable on the dimensions of the PCoA to obtain a graphical representation on the PCoA, which is known as External Logistic Biplot (ELB). This technique was proposed in its general form by [55] and the external approximation by [40]. The regression coefficients give the directions in the ordination diagram that better predict the existence of each indicator.

In another way, let π_{ij} = E(x_{ij}) be the predicted probability that the social indicator j is present at organization i and x_{ij} be the observed probability (0 or 1) from the configuration coordinates. The S-dimensional External Logistic Biplot is written as:

$$\pi_{ij} = \frac{e^{b_{jo}} + \Sigma_s b_{js} a_{is}}{\mathrm{I} + e^{b_{jo}} + \Sigma_s b_{js} a_{is}}$$

where a_{is} $(i = 1, \ldots, I)(s = 1, \ldots, S)$ are the principal coordinates and b_{js} (j = 1,...,J) $(s = 1, \ldots, S)$ are the LR coefficients for the $j-$ th indicator (binary variable) in the $s-$ th dimension. In logit scale:

$$logit(\pi_{ij}) = log(\frac{\pi_{ij}}{\mathrm{I} - \pi_{ij}}) = b_{jo} + \sum_{s=1}^{S} b_{js} a_{is} = b_{jo} + \mathbf{a}_i^t \mathbf{b}_j.$$

Then, $\mathbf{a}_i = (a_{i1}, \ldots, a_{iS})^t$ and $\mathbf{b}_j = (b_{j1}, \ldots, b_{jS})^t$ define a biplot for the logits. This is called External Logistic Biplot because the coordinates of them are calculated in an external procedure (LR on the PCoA). Normally, the companies are represented as points and the indicators as directed arrows indicating the direction of increasing expected probabilities.

The constants b_{jo} have been added because it is not possible to centre the data matrix in the same way as in linear biplots or PCA. The constant is the displacement of the gravity centre in the same way as it is the first ordination axis in Correspondence Analysis.

The model is a latent trait model for binary data, the row coordinates being the scores of the individuals on the latent trait. Although the biplot in the logit scale may be useful, it would be more interpretable in a probability scale.

A complete description of the biplot and its geometry can be found in [40,56] and some applications in [35,57–59]. New algorithms have been recently developed in [50].

The Binary Logistic Biplot summarizes the information of a set of binary variables in a few dimensions, allowing for the simultaneous interpretation of the whole set. It also permits the separation of signal and noise, extracting the interpretable information contained in the whole set.

The distance among points representing individuals (companies) is interpreted as similarity, thus allowing for the search of clusters of individuals with similar characteristics.

Angles among characters can be interpreted as correlations; two arrows pointing to the same direction correspond to positively correlated variables and arrows pointing to opposite directions correspond to negatively correlated variables. Arrows with an angle of 90 degrees correspond to non-correlated variables. It is also possible to interpret the variables responsible for the classification of the individuals.

Projections of company points onto indicator directions approximate the expected probability of the indicator be present on the company given the combination of the rest of the indicators, then allowing for the search of the indicators responsible for the configuration or grouping of the companies.

In summary, the approach uses the multivariate nature of the data, offering some advantages over the classical methods:

(i) The main patterns of variation are summarized in just a few dimensions.
(ii) The graphical representations permit not only global exploration of the main patterns and the variables associated with the discrimination, but also the direction of the association and the selection of small subsets that have a similar behaviour in relation to the discrimination.
(iii) It is possible to study the correlation structure among the binary variables.
(iv) It is possible to find combined gradients (or latent variables) that summarize the information provided by the whole set of variables.

To identify groups of companies with similar characteristics, Cluster Analysis (CA) can be used with the coordinates on the dimensions using, for example, the Ward method. The application of the Ward method of minimum variance generates the formation of clusters based on the individuals (companies). The biplot graphic representation allows for visualising the relationships between the clusters or companies and the indicators. For a correct interpretation, the parameters of [59] were considered.

The analysis can also be considered as some kind of Factor Analysis where the factors are the dimensions obtained from the PCoA. Factor loadings are generated form the indicator parameters to show how the companies in the sample relate to the factors [60].

ELB uses three indices to measure the quality of representation of each indicator on the graph: first, the p-value, it is relationship between the solution and each variable (deviance); second, the Nagelkerke pseudo R-squared [61]; and third the percentage of correct classifications, assuming that that the classification of presence occurs when the corresponding expected probability is higher than 0.5.

4. HJ-Biplot

The HJ biplot is essentially similar to correspondence analysis; however, it is applicable to continuous data rather than categorical data [62]. Now, the data matrix $\mathbf{X}$ contains the data of the percentages of each country. The HJ-Biplot [41] is a multidimensional data technique proposed as an alternative to improve the classic biplots introduced by [39]. The classic biplots graphically represent three or more variables in a space of reduced dimension [63], generally two. For a data matrix $\mathbf{X}$, the biplot graphical representation is made by markers (vectors) $\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_I$ for the rows and $\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_J$ for the columns of $\mathbf{X}$ in such a way that the inner product approximates the element x_{ij} of $\mathbf{X}$ as close as possible.

From an algebraic point of view, the Biplot method is based on the approximation of the data matrix $\mathbf{X}$ by one of lower rank q, where $q < r$ (with r being the rank of $\mathbf{X}$), through the singular value decomposition (SVD), which is defined as $\mathbf{X} = \mathbf{UDV}^T$, where $\mathbf{U}$ is a matrix whose column vectors are orthogonal and represent the eigenvectors of $\mathbf{XX}^T$, $\mathbf{V}$ is a matrix whose column vectors are orthogonal and correspond to the eigenvectors of $\mathbf{X}^T\mathbf{X}$, and $\mathbf{D}$ is a diagonal matrix containing the singular values.

The two-best known biplot factorizations developed by Gabriel are: the GH-Biplot and JK-Biplot. The GH-Biplot analyses the relationships between the columns (variables) with higher quality of representation (variables), while the JK-Biplot analyses the similarity between the rows (individuals) with higher quality of representation.

As an improvement alternative to the classic biplot, the HJ-Biplot maximizes the quality of representation of the rows and columns simultaneously in the same low dimensional space [57,62,64].

In this study, the main objective of the HJ-Biplot is to explain the relationship between the rows (countries) and the columns (indicators) based on the interpretation guidelines of the HJ-Biplot:

- It allows for identifying which countries have similar profiles. The closer they are to each other, the more similar profiles they have.
- It evaluates the relationships between the social aspects, according to the size of the cosines of the angles formed by the column vectors. Acute angles indicate a positive correlation, obtuse angles a negative relation, and right angles suggest no correlation.
- The classification of countries according to social indicators is made using the correlations with the factors as in the Factor Analysis.

5. Results

5.1. Exploratory Analysis

Prior to the multivariate analysis and behaviour prediction, a descriptive analysis of the geographical representation of the 158 companies was carried out (see Table 1).

Table 1. Distribution of the samples by countries.

Countries	Frequency		Countries	Frequency	
	Absolute (N)	Relative (%)		Absolute (N)	Relative (%)
Australia	5	3.16%	Mexico	1	0.63%
Belgium	2	1.27%	Netherlands	5	3.16%
Brazil	5	3.16%	Poland	1	0.63%
Canada	2	1.27%	Korea	10	6.33%
France	9	5.70%	Russia	4	2.53%
Germany	13	8.23%	Spain	5	3.16%
Hong Kong	3	1.90%	Sweden	2	1.27%
India	3	1.90%	Switzerland	6	3.80%
Ireland	1	0.63%	Taiwan	4	2.53%
Italy	2	1.27%	Thailand	1	0.63%
Japan	18	11.39%	United Kingdom	4	2.53%
China	19	12.03%	United States	33	20.89%

Table 2 shows the descriptive statistics of CSR practices, specifically of the social dimension divided by aspect. The most frequently reported aspects are training and education (LA8) with 74.26%, diversity and equal opportunity (LA12) with 81.65% and anti-corruption (SO3, SO4, SO5) with 61.39%. Conversely, companies lack in the management of practices related to security practices (HR7) with 26.58% and indigenous rights (HR8) with 20.89%.

Table 2. Descriptive statistics of social indicators.

Sub-Categories	Aspects	Code	% Reported
Labour practices and decent work	Employment	LA1, LA2, LA3	57.17
	Labour/management relations	LA4	40.51
	Occupational health and safety	LA5, LA6, LA7, LA8	51.42
	Training and education	LA9, LA10, LA11	74.26
	Diversity and equal opportunity	LA12	81.65
	Equal remuneration for women and men	LA13	43.67
	Supplier assessment for labour practices	LA14, LA15	44.30
	Labour practices grievance mechanisms	LA16	41.77
Human rights	Investment	HR1, HR2	42.41
	Non-discrimination	HR3	43.04
	Freedom of association and collective bargaining	HR4	42.41
	Child labour	HR5	52.53
	Forced or compulsory labour	HR6	53.80
	Security practices	HR7	26.58
	Indigenous rights	HR8	20.89
	Assessment	HR9	33.54
	Supplier human rights assessment	HR10, HR11	46.20
	Human rights grievance mechanisms	HR12	36.08
Society	Local communities	SO1, SO2	54.75
	Anti-corruption	SO3, SO4, SO5	61.39
	Public policy	SO6	43.04
	Anti-competitive behaviour	SO7	38.61
	Compliance	SO8	48.73
	Supplier assessment for impacts on society	SO9, SO10	40.82
	Grievance mechanisms for impacts on society	SO11	31.01
Product responsibility	Customer health and safety	PR1, PR2	45.89
	Product and service labelling	PR3, PR4, PR5	48.52
	Marketing communications	PR6, PR7	32.59
	Customer privacy	PR8	55.06
	Compliance	PR9	39.24

Figure 1 allows us to observe in a percentage which social indicators are reported more and less frequently by the largest companies in the world. The indicators most disclosed by the companies analysed in the Labour practices and decent work subcategory are LA10 and LA12 with 82%. The least reported indicator in this subcategory is LA7 with 39%.

In the Human Rights subcategory, the indicator most reported by companies was HR6 with 54%. On the contrary, HR8 is the social indicator less widely disclosed by large companies with 21%.

For Society, the most frequently reported indicator is SO4 with 80%. The least reported is SO11 with 31%.

The Product Responsibility subcategory has as the most-reported indicator PR5 with 70%, and the least reported are PR4 and PR6, with 32% for both.

5.2. External Logistic Biplot

The first result of the External Logistic Biplot is the global goodness of fit with 80.89 per cent, high enough for the correct biplot classification, so the two-dimensional solution is necessary to explore the important characteristics of the results. The percentage of correctly classified variables is on average 77.47% goodness of fit.

Table 3 shows the corporate social reporting indicators where the R-squared values are as high as 5; the *p*-value of the logistic regression is used to test the relationship between the solution and each variable (via deviance); and the percentage of correct classifications are higher than 70%.

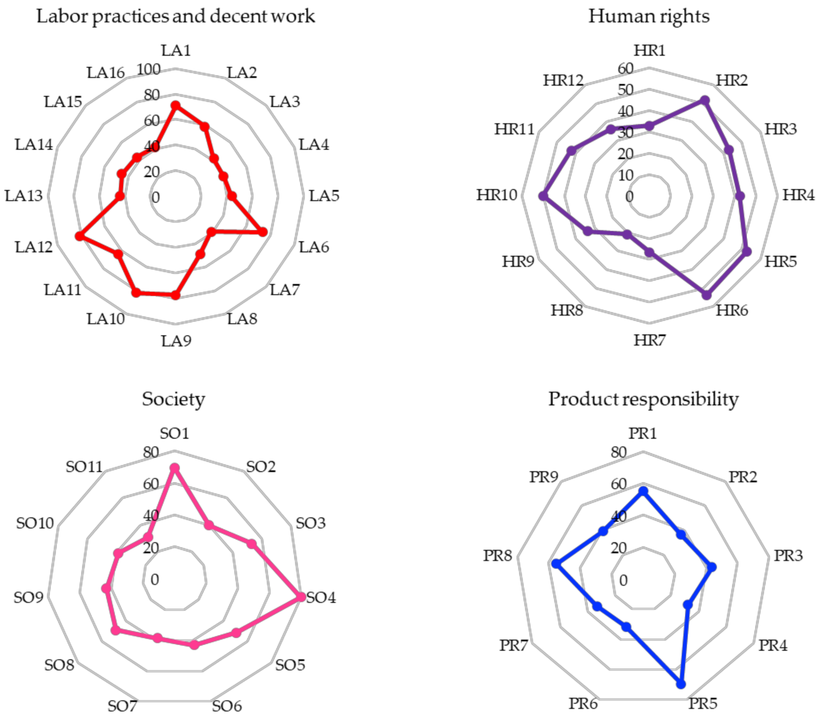

Figure 1. Frequency of disclosure of each social indicator por sub-categories.

Table 3. Social indicators with higher quality of representation.

Variables	Deviance	*p*-Value	R2	% Correct
LA13	92.31	0.000	0.59	80.38
LA14	136.24	0.000	0.77	86.71
LA15	136.84	0.000	0.77	87.98
LA16	86.93	0.000	0.57	81.01
HR4	82.46	0.000	0.55	78.48
HR5	77.52	0.000	0.52	77.85
HR7	73.69	0.000	0.53	84.81
HR8	77.88	0.000	0.58	85.44
HR10	138.05	0.000	0.77	87.98
HR11	115.09	0.000	0.69	84.81
HR12	101.51	0.000	0.64	83.54
SO9	145.31	0.000	0.80	87.34
SO10	108.12	0.000	0.66	85.44
SO11	95.85	0.000	0.63	84.81
PR4	79.03	0.000	0.54	82.91

In Figure 2, the indicators are distinguished with a different colour depending on their appearance. The first factorial axis is characterized by the indicators of products responsibility (PR), and is represented in green, social aspects (SO) in red, and in blue those corresponding to human rights (HR). Regarding the second factorial axis, they are the indicators of labour practices and decent work (LA) that define it, in purple. Based on the direction of the social indicators, the sustainability gradient from the left (less) to the right (more) has been defined. In this sense, on the left side of factorial axis 2 are the companies that report indicators of social aspect less frequently. On the other hand, in quadrants 1–4, the companies with the greatest social disclosure are located.

Additionally, clusters have been created in the External Logistic Biplot (Figure 3). The companies have been grouped according to the similarities and differences in their behaviour with respect to the information reported through the GRI index, resulting three sustainability profiles.

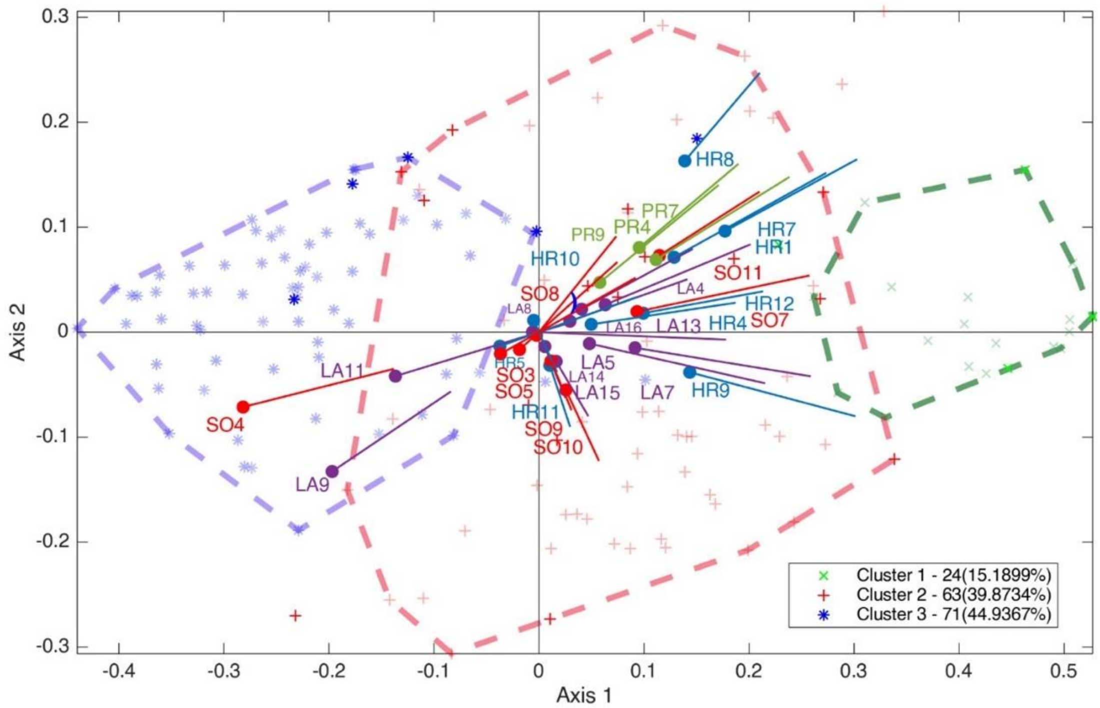

Figure 2. External Logistic Biplot with cluster: disclosure of social indicators.

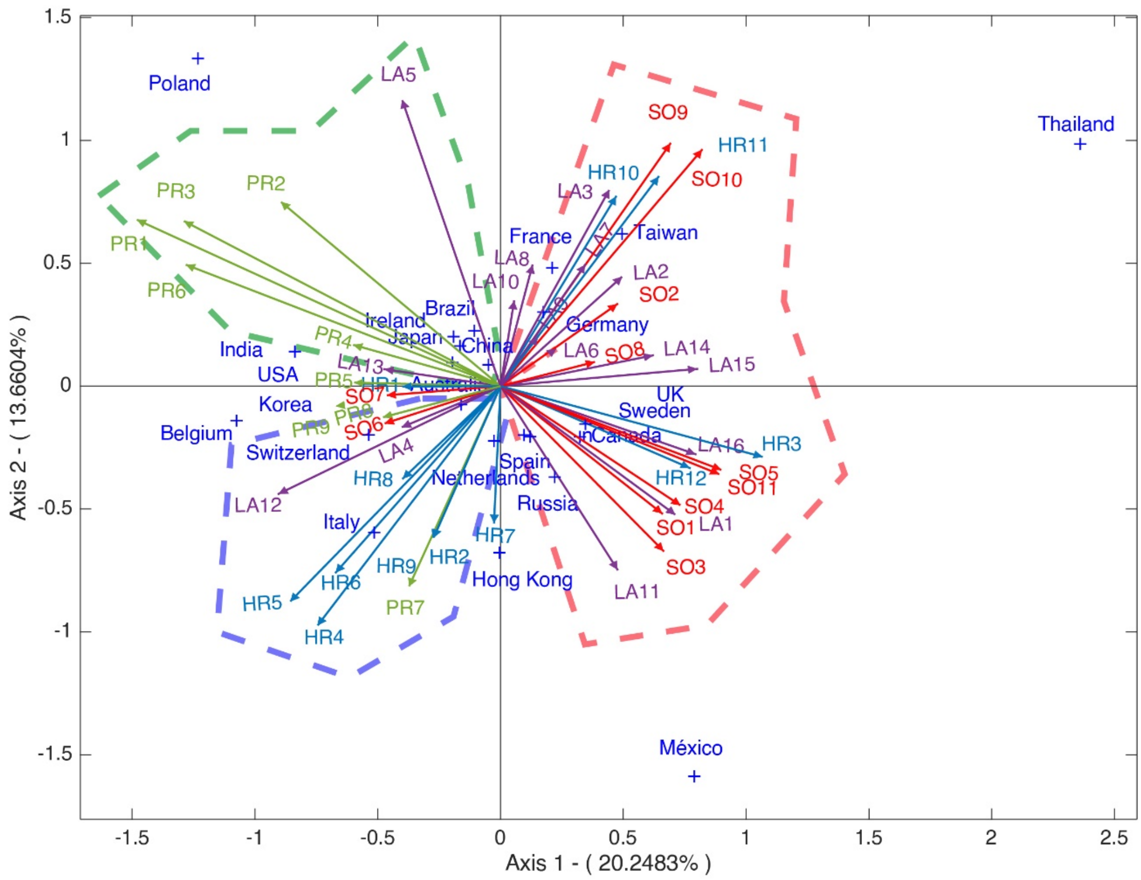

Figure 3. HJ-Biplot Cluster: countries with indicators.

Cluster 1 groups the companies with the greatest commitment to CSR, by reporting social indicators more frequently; this cluster is coloured in green. This is the smallest cluster, with 15.19% of the companies analysed.

Cluster 2 is made up of the companies that most frequently disclose social indicators, except LA11, LA9 and SO4. We can see this cluster in red (39.87% of the companies).

Cluster 3 includes the companies (44.94% of all companies) that report the social dimensions less frequently, mainly LA11, LA9 and SO4, which is why it lacks sustainability (blue cluster).

5.3. HJ-Biplot

The graphic representation of the HJ-Biplot illustrates in a two-dimensional space the indicators in vector form and the countries as points. The detailed visualisation of Figure 3 is useful to know the behaviour of the companies from a national perspective, based on the disclosure of social indicators.

The percentage of variance explained by the two main axes is 33.09%, which allows us to work with the first factorial plan (2 dimensions) for this analysis. Most of the information is provided by the first factorial axis since it has the highest eigenvalue (15.38) than the second (10.38).

The first and fourth quadrant (red line) show the countries corresponding to the companies that most frequently disclose the aspects of society (SO), human resources (HR) and labour practices and decent work (LA). The countries that present CSR in these aspects are Germany, Sweden, Canada, Spain, France, Russia, Mexico and Thailand.

The second quadrant (green line) shows the countries of the companies that disclose most frequently in relation to Product Responsibility (PR). The United States, Brazil, China, Japan, Australia, India and Poland are the countries with the highest diffusion in PR.

In the third quadrant (blue line), the Human Resources (HR) indicators are projected mostly, with indicators reported more frequently by companies based in the countries of Korea, Belgium, Switzerland, Italy, the Netherlands and Hong Kong.

6. Discussion

This work has a dual objective, explore the performance of two of the most popular techniques in Multivariate statistics: External Logistic Biplot and the HJ-Biplot for the analysis of the structure of the data and evaluate the commitment to CSR that the world's largest companies have, by inspecting the indicators of the social dimension reported to the GRI with these multivariate Machine Learning techniques. The theoretical contribution of this research means an excellent advance to place the biplots methods as effective techniques of Machine Learning in the analysis of sustainability issues.

To carry out the analysis, we used a sample of 158 companies that appear in the Fortune Global 500 ranking. The results of this study allow a broad and detailed view of the CSR commitment implemented by the largest companies in the world, highlighting the information disclosed by companies in the annual sustainability reports published through the Global Reporting Initiative (GRI). Previous literature evidences the voluntary participation of companies in the dissemination of information on CSR practices that they manage [34,65].

The exploratory analysis confirms that 37.5% of the social indicators are reported in more than 50% of the sustainability reports generated by the main corporations worldwide, according to the GRI Sustainability Index, while 62.5% of the indicators are reported in fewer. Our findings are consistent with previous research, which argues that the disclosure of information by large corporations in relation to their practices in the social area turns out to be scarce, affecting CSR globally [66–68]. In this sense, the training and education and diversity and equal opportunity aspects are reported more frequently by the largest companies in the world. On the contrary, there is a lack of disclosure in indigenous rights and security practices.

The results obtained from the first multivariate analysis, specifically the External Logistic Biplot, suggest three groups based on the similar behaviour of the study companies. Cluster 1 encompasses 15.19% of the companies, which show high commitment in CSR, disclosing social indicators very frequently. Cluster 2 groups 39.87% of the corporations, which have a medium-high level of sustainability. Cluster 3, represented by 44.94% of the sample, lacks a sustainable profile.

The HJ-Biplot multivariate technique has been used in previous studies [35,59,69,70] to analyse CSR commitment in relation to social performance at the country level. Following this methodology, we have determined the commitment to CSR, based on the analysis of the information disclosed in the sustainability reports, specifically on social performance by geographic region [36].

The External Logistics Biplot has allowed us to know the behaviour of large companies in terms of sustainability; specifically, it reveals which indicators are reported most frequently, as well as the least disclosed. The results obtained from the HJ-Biplot analysis indicate the correlations between the 48 social indicators, as well as their disclosure by geographic region.

This research presents convenient implications for the literature related to the CSR commitment of the largest companies worldwide through the management of their social performance business practices. The adequate combination of the statistical techniques applied, as well as the selection of the data and the adequate interpretation of the results, offers a broad and deep perspective to the interest groups on the social commitment that the most remunerated global companies currently have, facilitating the identification of the implemented practices and the ones that need to be managed the most.

We discovered that both machine learning algorithms are extremely competitive and practical to apply in CSR since they are simple to implement and work well with relatively big data sets.

Our work has some limitations, which offer opportunities for future research. The first is related to the information analysed since we have only used the GRI sustainability index as a reference, in the social dimension to be precise, so it would be interesting to analyse information disclosed through another sustainability index or consider the GRI index in its entirety. The second is in relation to the size of the sample due to the established criteria; it would be significant to carry out a similar study with a larger sample size. Finally, the third is in relation to the version of the GRI guide used, which has undergone updates, so it would be novel to analyse CSR considering the most current version of the GRI index.

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Abbreviations

The following abbreviations are used in this manuscript:

GRI	Global Reporting Initiative
ELB	External Logistic Biplot
CSR	Corporate Social Responsibility
CA	Cluster analysis
PCoA	Principal Coordinates Analysis
SVD	Singular Value Decomposition
PCA	Principal Component Analysis
LR	Linear Regression

Appendix A. Social Indicators Dimensions and Codes

Sub-Category: Labour Practices and Decent Work (LA)	
Total number and rates of new employee hires and employee turnover by age group, gender and region	LA1
Benefits provided to full-time employees that are not provided to temporary or part-time employees by significant locations of operation	LA2
Return to work and retention rates after parental leave by gender	LA3
Minimum notice periods regarding operational changes, including whether these are specified in collective agreements	LA4
Percentage of total workforce represented in formal joint management–worker health and safety committees that help monitor and advise on occupational health and safety programs	LA5
Type of injury and rates of injury, occupational diseases, lost days, absenteeism, and total number of work-related fatalities, by region and by gender	LA6
Workers with high incidence or high risk of diseases related to their occupation	LA7
Health and safety topics covered in formal agreements with trade unions	LA8
Average hours of training per year per employee by gender, and by employee category	LA9
Programs for skills management and lifelong learning that support the continued employability of employees and assist them in managing career endings	LA10
Percentage of employees receiving regular performance and career development reviews, by gender and by employee category	LA11
Composition of governance bodies and breakdown of employees per employee category according to gender, age group, minority group membership, and other indicators of diversity	LA12
Ratio of basic salary and remuneration of women to men by employee category, by significant locations of operation	LA13
Percentage of new suppliers that were screened using labour practices criteria	LA14
Significant actual and potential negative impacts for labour practices in the supply chain and actions taken	LA15
Number of grievances about labour practices filed, addressed and resolved through formal grievance mechanisms	LA16
Sub-Category: Human Rights (HR)	
Total number and percentage of significant investment agreements and contracts that include human rights clauses or that underwent human rights screening	HR1
Total hours of employee training on human rights policies or procedures concerning aspects of human rights that are relevant to operations, including the percentage of employees trained	HR2
Total number of incidents of discrimination and corrective actions taken	HR3
Operations and suppliers identified in which the right to exercise freedom of association and collective bargaining may be violated or at significant risk, and measures taken to support these rights	HR4
Operations and suppliers identified as having significant risk for incidents of child labour, and measures taken to contribute to the effective abolition of child labour	HR5
Operations and suppliers identified as having significant risk for incidents of forced or compulsory labour, and measures to contribute to the elimination of all forms of forced or compulsory labour	HR6
Percentage of security personnel trained in the organization's human rights policies or procedures that are relevant to operations	HR7
Total number of incidents of violations involving rights of indigenous peoples and actions taken	HR8
Total number and percentage of operations that have been subject to human rights reviews or impact assessments	HR9
Percentage of new suppliers that were screened using human rights criteria	HR10
Significant actual and potential negative human rights impacts in the supply chain and actions taken	HR11
Number of grievances about human rights impacts filed, addressed, and resolved through formal grievance mechanisms	HR12

Sub-Category: Society (SO)	
Percentage of operations with implemented local community engagement, impact assessments, and development programs	SO1
Operations with significant actual and potential negative impacts on local communities	SO2
Total number and percentage of operations assessed for risks related to corruption and the significant risks identified	SO3
Communication and training on anti-corruption policies and procedures	SO4
Confirmed incidents of corruption and action taken	SO5
Total value of political contributions by country and recipient/beneficiary	SO6
Total number of legal actions for anti-competitive behaviour, anti-trust, and monopoly practices and their outcomes	SO7
Monetary value of significant fines and total number of non-monetary sanctions for non-compliance with laws and regulations	SO8
Percentage of new suppliers that were screened using criteria for impacts on society	SO9
Significant actual and potential negative impacts on society in the supply chain and actions taken	SO10
Number of grievances about impacts on society filed, addressed, and resolved through formal grievance mechanisms	SO11
Sub-Category: Product Responsibility (Pr)	
Percentage of significant product and service categories for which health and safety impacts are assessed for improvement	PR1
Total number of incidents of non-compliance with regulations and voluntary codes concerning the health and safety impacts of products and services during their life cycle, by type of outcomes	PR2
Type of product and service information required by the organisation's procedures for product and service information and labelling, and percentage of significant product and service categories subject to such information requirements	PR3
Total number of incidents of non-compliance with regulations and voluntary codes concerning product and service information and labelling, by type of outcomes	PR4
Results of surveys measuring customer satisfaction	PR5
Sale of banned or disputed products	PR6
Total number of incidents of non-compliance with regulations and voluntary codes concerning marketing communications, including advertising, promotion, and sponsorship, by type of outcomes	PR7
Total number of substantiated complaints regarding breaches of customer privacy and losses of customer data	PR8
Monetary value of significant fines for non-compliance with laws and regulations concerning the provision and use of products and services	PR9

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