mathematics

MDPI

Systematic Review

HJ–BIPLOT: A Theoretical and Empirical Systematic Review of Its 38 Years of History, Using Text Mining and LLMs

Roberto Cascante-Yarlequé [1,2,*], Purificación Galindo-Villardón [1,2,3], Fabricio Guevara-Viejó [2], José Luis Vicente-Villardón [1] and Purificación Vicente-Galindo [1,2]

[1] Department of Statistics, University of Salamanca, 37008 Salamanca, Spain
[2] Centro de Estudios Estadísticos, Universidad Estatal de Milagro (UNEMI), Milagro 091050, Ecuador
[3] Escuela Superior Politécnica del Litoral (ESPOL), Centro de Estudios e Investigaciones Estadísticas (CEIE), Campus Gustavo Galindo, Km. 30.5 Vía Perimetral, P.O. Box 09-01-5863, Guayaquil 090112, Ecuador
* Correspondence: rcascant@usal.es

Abstract: The HJ-Biplot, introduced by Galindo in 1986, is a multivariate analysis technique that enables the simultaneous representation of rows and columns with high-quality visualization. This systematic review synthesizes findings from 121 studies on the HJ-Biplot, spanning from 1986 to December 2024. Studies were sourced from Scopus, Web of Science, and other bibliographic repositories. This review aims to examine the theoretical advancements, methodological extensions, and diverse applications of the HJ-Biplot across disciplines. Text mining was performed using IRAMUTEQ software, and Canonical Biplot analysis was conducted to identify four key evolutionary periods of the technique. A total of 121 studies revealed that health (14.9%), sustainability (11.6%), and environmental sciences (12.4%) are the primary areas of application. Canonical Biplot analysis showed that two main dimensions explained 80.24% of the variability in the dataset with Group 4 (2016–2024) achieving the highest cumulative representation (98.1%). Recent innovations, such as the Sparse HJ-Biplot and Cenet HJ-Biplot, have been associated with contemporary topics like COVID-19, food security, and sustainability. Artificial intelligence (ChatGPT 3.5) enriched the analysis by generating a detailed timeline and identifying emerging trends. The findings highlight the HJ-Biplot's adaptability in addressing complex problems with significant contributions to health, management, and socioeconomic studies. We recommend future research explore hybrid applications of the HJ-Biplot with machine learning and artificial intelligence to further enhance its analytical capabilities and address its current limitations.

Keywords: HJ-Biplot; multivariate analysis; data visualization; systematic review; methodological extensions; AI

MSC: 62H25; 68T50

check for updates

Academic Editor: Iraklis Varlamis

Received: 23 January 2025
Revised: 28 March 2025
Accepted: 29 March 2025
Published: 7 June 2025

Citation: Cascante-Yarlequé, R.; Galindo-Villardón, P.; Guevara-Viejó, F.; Vicente-Villardón, J.L.; Vicente-Galindo, P. HJ-BIPLOT: A Theoretical and Empirical Systematic Review of Its 38 Years of History, Using Text Mining and LLMs. *Mathematics* **2025**, *13*, 1913. https://doi.org/10.3390/math13121913

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Ruben Gabriel, in his seminal paper of 1971, introduced the concept of a Biplot, which is a graphical representation of matrices that combines the visualization of rows and columns using points and vectors, respectively [1]. This method allows the visualization of relationships between different variables and observations in a data matrix, offering a powerful tool for *principal component analysis* (PCA). The Biplot facilitates the identification of patterns, groups, and relationships within the data, providing a visual interpretation that

complements traditional analytical techniques. Its implementation has enabled the better understanding and communication of complex structures in multivariate datasets [2].

As shown in Figure 1, Gabriel built upon the previous work of several key authors in the fields of Mathematics and Statistics. The *singular value decomposition* (SVD) of matrices, which is fundamental to the `Biplot`, dates back to Eckart and Young, who developed principal transformations for non-Hermitian matrices [3]. Moreover, Gabriel references the work of Householder and Young, who addressed matrix approximation and latent roots, laying the groundwork for matrix factorization techniques used in his method [4]. These studies provided the mathematical framework necessary for the development of Gabriel's Biplots.

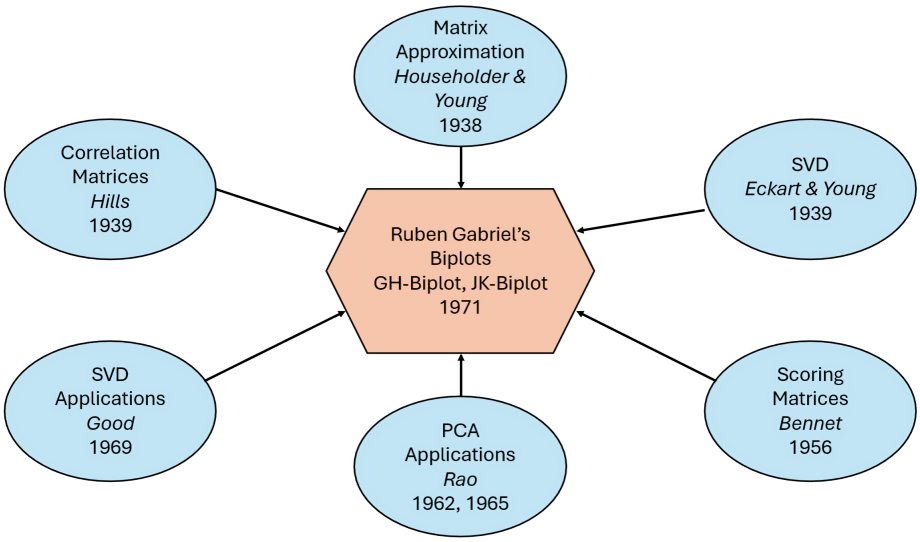


Figure 1. Techniques used by Ruben Gabriel to develop Biplot methods [1–10].

The influence of Rao is also notable in Gabriel's work. Rao, in [5–7], developed advanced statistical methods for biometric research and linear statistical inference, including the use and interpretation of principal component analysis in applied research. These methods and principles were essential for Gabriel to formulate and apply the `Biplot` effectively, adapting these techniques to enhance the visualization and analysis of multivariate data. The application of these principles allowed Gabriel to create a more accessible and practical tool for researchers.

Another significant author mentioned by Gabriel is Good [8], who explored applications of singular value decomposition in matrices, providing a deeper understanding of the relationships between matrix elements. Good's ideas on matrix interpretation and complex data structure directly influenced Gabriel's ability to visualize *high-rank* matrices using Biplots. Gabriel acknowledges the influence of authors such as Hill [9] and Bennett [10], who explored large correlation matrices and independent parameters in score matrices, respectively. These studies provided a background on the importance of visualizing complex data structures and how these visualizations can reveal hidden patterns and meaningful relationships. The integration of these ideas allowed Gabriel to consolidate his `Biplot` method, creating a versatile and widely applicable tool for multivariate data analysis [8–10].

In [1], Gabriel developed an innovative mathematical methodology to represent matrices through the `Biplot`. Based on the premise that any matrix $\mathbf{Y}$ of rank r can be factorized into two *smaller-dimensional* matrices, he proposed the following factorization:

$$\mathbf{Y} = \mathbf{G}\mathbf{H}^{\mathrm{T}}$$

where $\mathbf{G}$ is an $n \times r$ matrix and $\mathbf{H}$ is an $m \times r$ matrix. This factorization is *not unique* and can be written for each element y_{ij} of matrix $\mathbf{Y}$ as the inner product of the corresponding vectors:

$$y_{ij} = g_i^{\mathrm{T}} h_j$$

where g_i is the i-th row of $\mathbf{G}$ and h_j is the j-th row of $\mathbf{H}$. To approximate matrices of rank higher than two, Gabriel used the singular value decomposition (SVD), which is expressed as shown below:

$$\mathbf{Y} = \sum_{a=1}^{r} \lambda_a p_a q_a^{\mathrm{T}}$$

where λ_a represents the singular values, p_a represents the singular vectors of the columns and q_a^{T} represents the singular vectors of the rows. A special case of this is the rank-two approximation of a matrix $\mathbf{Y}$, which is given as shown below:

$$\mathbf{Y}_{(2)} = \lambda_1 p_1 q_1^{\mathrm{T}} + \lambda_2 p_2 q_2^{\mathrm{T}}$$

The *goodness of fit* of this approximation is measured by the following.

$$\mathbf{P}(\mathbf{Y}_{(2)}) = \frac{\lambda_1^2 + \lambda_2^2}{\sum_{a=1}^{r} \lambda_a^2}$$

Additionally, Gabriel proposed two types of factorizations for Biplots: one that satisfies the condition $\mathbf{H}^{\mathrm{T}}\mathbf{H} = \mathbf{I}_2$ (`JK-Biplot`) and another that satisfies $\mathbf{G}^{\mathrm{T}}\mathbf{G} = \mathbf{I}_2$ (`GH-Biplot`), where $\mathbf{I}_2$ is the *identity matrix* of order 2. In the former, relationships between rows are directly represented by the g vectors:

$$\mathbf{Y}^{\mathrm{T}}\mathbf{Y} = \mathbf{H}\mathbf{H}^{\mathrm{T}}$$

In the latter, relationships between columns are represented by the h vectors:

$$\mathbf{Y}\mathbf{Y}^{\mathrm{T}} = \mathbf{G}\mathbf{G}^{\mathrm{T}}$$

For matrices of rank higher than two, the approximation via SVD and selection of principal components allows for the graphical representation of multivariate relationships in an understandable manner. In his analysis, Gabriel also introduced the concept of specific metrics to make the factorization and `Biplot` unique except for rotations and reflections that do not change the relationships between vectors, such as the following metric:

$$\mathbf{Y}\mathbf{M}\mathbf{Y}^{\mathrm{T}} = \mathbf{G}\mathbf{G}^{\mathrm{T}}$$

One must choose $\mathbf{H}$ such that

$$\mathbf{H}^{\mathrm{T}}\mathbf{M}\mathbf{H} = \mathbf{I_2}$$

This mathematical implementation allows Biplots to be used in a wide range of applications in multivariate data analysis, improving both the visual and analytical interpretation of complex data structures.

The `GH-Biplot` and `JK-Biplot` are two methods used for the graphical representation of multivariate matrices each with a specific focus on the *quality of representation*. The `GH-Biplot` focuses on obtaining the maximum representation quality for variables, which is crucial in applications such as genomic data analysis, market research, and quality control in manufacturing. In contrast, the `JK-Biplot` seeks to best represent rows or individuals, being useful in customer segmentation, student performance analysis,

and user behavior analysis. Both methods share the common goal of providing a clear and comprehensible visual representation of the data, but they differ in their main focus [1].

While the `GH-Biplot` is applied in contexts where the precise representation of variables is critical, the `JK-Biplot` is better suited for analyzing and comparing individuals or observations. Despite these differences, both methods are widely applicable in multivariate data analysis, providing valuable tools for the visualization and understanding of complex data.

For matrices $\mathbf{Y}$ of observations of n units in m variables, it is essential to subtract the mean of each variable to center the data before proceeding with the analysis. Gabriel uses the estimated *variance–covariance* matrix $\mathbf{S}$ to capture the variability and the linear relationships between the variables. This matrix is defined as

$$\mathbf{S} = \frac{1}{n}\mathbf{Y}^{\mathrm{T}}\mathbf{Y}$$

where $\mathbf{Y}$ is the centered data matrix, $\mathbf{Y}^{\mathrm{T}}$ is the transpose of $\mathbf{Y}$, and n is the number of observations. The matrix $\mathbf{S}$ provides a measure of how the variables co-vary, which is essential for multivariate analysis. The standardized distances between units i and e are calculated to understand the relative differences between observations in multivariate space. This *distance* is defined as

$$d_{ie}^2 = (y_i - y_e)^{\mathrm{T}}\mathbf{S}^{-1}(y_i - y_e)$$

where y_i and y_e are row vectors corresponding to units i and e, and $\mathbf{S}^{-1}$ is the inverse of the variance–covariance matrix. This formula allows measuring the similarity between observations, adjusting for the variance and correlations among variables.

In a `Biplot`, standardized distances can be approximated to simplify the graphical representation. Gabriel proposes the following approximation:

$$d_{ie}^2 \approx (g_i - g_e)^{\mathrm{T}}(g_i - g_e)$$

where g_i and g_e are vectors that represent the observations in the reduced space of the `Biplot`. This approximation facilitates visual interpretation, allowing for a direct comparison of the distances between points in the `Biplot`. The `Biplot` also allows for the visual representation of the variances and covariances of the variables. These equations enable the `Biplot` to visually represent the statistical relationships between variables, facilitating the interpretation of variance, covariance, and correlation in the data [11]. The vectors h in the `Biplot` indicate how the variables co-vary and provide an intuitive way to visualize associations between them. This is especially useful in identifying patterns and relationships in complex data, making the `Biplot` a valuable tool for multivariate analysis.

Despite the fact that Gabriel's Biplots are powerful tools for the visualization of multivariate data, they have a crucial limitation: they only allow for the maximum quality of representation for either variables or individuals *but not both simultaneously*. This detail was identified by Galindo in 1986 [12], who developed the `HJ-Biplot` technique. This technique addresses this limitation by maximizing the quality of representation for both variables and individuals in the same plane or low-dimensional space. This innovation allows for a more complete and balanced interpretation of the data, facilitating a more robust and detailed analysis of multivariate structures.

The `HJ-Biplot` technique shares similar principles with Benzecri's *correspondence analysis* (CA) [13] and *multiple correspondence analysis* (MCA) but with extended versatility that allows its application to any type of data, not just frequencies [12]. As shown in Figure 2, the `HJ-Biplot` is based on singular value decomposition (SVD) and allows projecting

both individuals and variables in the same space, providing a graphical representation that facilitates the interpretation of multivariate relationships.

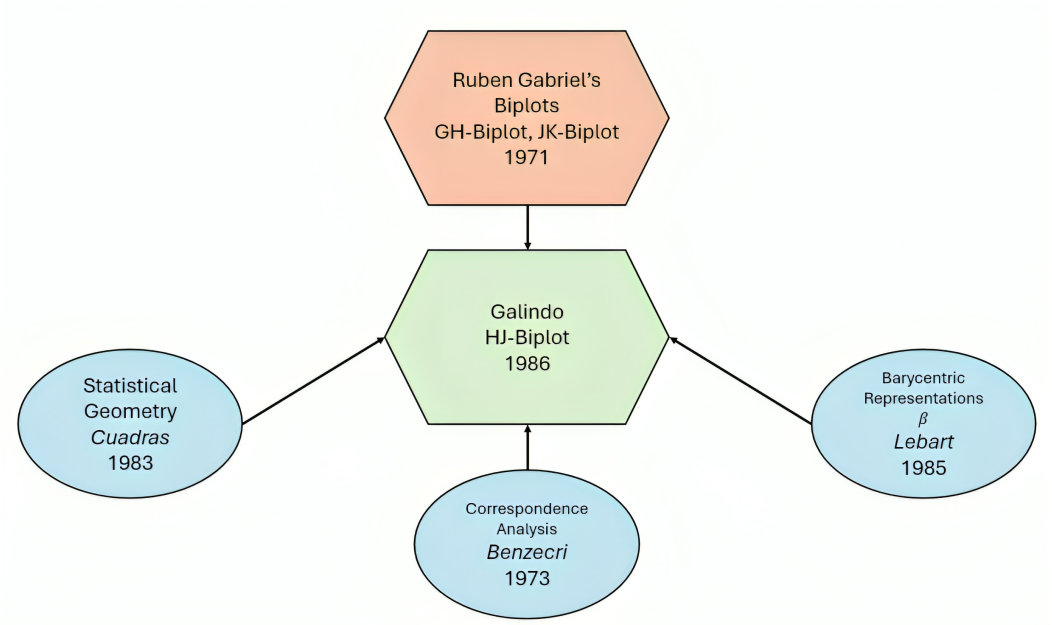


Figure 2. Techniques used by Galindo to develop the `HJ-Biplot` technique [12–14].

Unlike CA and MCA, which are primarily designed for categorical data and contingency tables, the `HJ-Biplot` can handle continuous, categorical, and mixed data. This flexibility makes it particularly useful in studies where variables of different types must be analyzed simultaneously [14].

The `HJ-Biplot` stands out for its ability to provide a symmetric representation of rows and columns, ensuring that the quality of representation is optimal for both clouds. This contrasts with other Biplots where the quality of representation is not the same for rows and columns. The technique maximizes the quality of the representation using appropriate metrics in the row and column spaces, allowing for the accurate interpretation of relative positions and interrelations.

Additionally, the `HJ-Biplot` can incorporate external information, such as additional categorical variables, to enrich the analysis and provide deeper context. This capability makes it a powerful tool for exploring and visualizing complex data, facilitating the identification of hidden patterns and trends.

Given a data matrix X, with dimensions $n \times p$, where n is the number of individuals and p is the number of variables, this matrix contains the observations of each individual for each variable. It is common to center the matrix X to eliminate the effect of different average levels of the variables. This is accomplished by subtracting the mean of each column (variable) from each of the elements in that column, thus obtaining the *centered matrix* $\mathbf{X} = X - \mathbf{1}\mathbf{m}^{\mathrm{T}}$, where $\mathbf{1}$ is a column vector of ones of length n and $\mathbf{m}$ is a vector of means of length p.

The centered matrix $\mathbf{X}$ is decomposed using SVD. This decomposition is a generalization of *eigenvalue* and *eigenvector* decomposition for non-square matrices. The SVD of $\mathbf{X}$ is expressed as $\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathrm{T}}$, where $\mathbf{U}$ is an orthogonal matrix with dimensions $n \times r$, whose column vectors are the left singular vectors; $\mathbf{D}$ is a diagonal matrix of dimensions $r \times r$ with the singular values of $\mathbf{X}$ on its diagonal; and $\mathbf{V}$ is an orthogonal matrix with dimensions $p \times r$, whose column vectors are the right singular vectors. In practice, the first k singular values that explain the majority of the variability in the data are selected. Thus, the first k columns of $\mathbf{U}$ and $\mathbf{V}$ and the first k singular values of $\mathbf{D}$ are selected.

The *coordinates of the individuals* in the reduced space are obtained by multiplying $\mathbf{U}_k$ by $\mathbf{D}_k$, resulting in $\mathbf{G} = \mathbf{U}_k\mathbf{D}_k$. Similarly, the coordinates of the variables are obtained by multiplying $\mathbf{V}_k$ by $\mathbf{D}_k$, obtaining $\mathbf{H} = \mathbf{V}_k\mathbf{D}_k$. In the `HJ-Biplot`, both individuals (rows) and variables (columns) are represented in the same two-dimensional or three-dimensional space, if applicable. The coordinates $\mathbf{G}$ and $\mathbf{H}$ are used to plot these points on a graph. The interpretation of the relative positions of the points is key in the `HJ-Biplot`: the proximity between points of individuals indicates *similarities* between them, while the orientation and length of the vectors of the variables indicate the direction and magnitude of their influence on the data.

The orthogonal projection of an individual's point onto a variable vector approximates the value of the individual on that variable. The *quality of the representation* in the `HJ-Biplot` can be evaluated using the proportion of the variability explained by the selected singular values. The sum of the squares of the selected singular values, divided by the sum of the squares of all singular values, provides a measure of the quality of the representation. This quality is expressed as follows:

$$\frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{r} \lambda_i^2}$$

where λ_i represents the singular eigenvalues. The `HJ-Biplot` also allows the incorporation of external information to enrich the analysis. This can be accomplished by including additional categorical variables that were not in the original dataset. These additional variables are projected into the same space, providing additional context for interpretation [15]. Interpretation of the `HJ-Biplot` involves examining the relative positions of the individuals and variables on the graph. Some key questions include the following. Which individuals are close to each other, and what does this mean in terms of the variables? Which variables are strongly correlated as indicated by nearby vectors? Which individuals are most influenced by specific variables as reflected in the proximity of their projections on the graph?

Table 1 below evaluates three `Biplot` techniques: `GH-Biplot`, `JK-Biplot`, and `HJ-Biplot`, in terms of their *global goodness of fit*, for rows and columns. Each technique is analyzed using specific mathematical formulas that measure the proportion of the total variability explained. For the `GH-Biplot`, the global goodness of fit is calculated as the sum of the squares of the first k singular values (λ_i) divided by the sum of the squares of all singular values. This global measure provides an overview of the representation quality. The goodness of fit for rows in the `GH-Biplot` is simplified as $2/r$, where r is the number of retained dimensions, while for the columns, the proportion of variability explained by the first two singular values is used over the total.

Table 1. Comparison of goodness of fit between `GH-Biplot`, `JK-Biplot`, and `HJ-Biplot`.

Technique	Global Fit	Rows Fit	Columns Fit
`GH-Biplot`	$\frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{r} \lambda_i^2}$	$\frac{2}{r}$	$\frac{\lambda_1^2 + \lambda_2^2}{\sum_{i=1}^{r} \lambda_i^2}$
`JK-Biplot`	$\frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{r} \lambda_i^2}$	$\frac{\lambda_1^2 + \lambda_2^2}{\sum_{i=1}^{r} \lambda_i^2}$	$\frac{2}{r}$
`HJ-Biplot`	$\frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{r} \lambda_i^2}$	$\frac{\lambda_1^2 + \lambda_2^2}{\sum_{i=1}^{r} \lambda_i^2}$	$\frac{\lambda_1^2 + \lambda_2^2}{\sum_{i=1}^{r} \lambda_i^2}$

The `JK-Biplot`, on the other hand, uses the same formula for global goodness of fit as the `GH-Biplot`—that is, the proportion of total variability explained by the first k

singular values. However, it differs in how it calculates the goodness of fit for rows and columns. For the rows, the `JK-Biplot` employs the following formula:

$$\frac{\lambda_1^2 + \lambda_2^2}{\sum_{i=1}^{r} \lambda_i^2} \tag{1}$$

which implies a more accurate representation based on the first two singular values. For the columns, the technique simplifies the goodness of fit to $2/r$, which is similar to what the `GH-Biplot` does for the rows. This difference in the formulas reflects an alternative approach to data representation and adjustment.

The `HJ-Biplot` is notable for its symmetry in the representation of rows and columns. It uses the same formula for global *goodness of fit* as the other two techniques:

$$\frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{r} \lambda_i^2}$$

ensuring a consistent measure of explained variability. For both rows and columns, the `HJ-Biplot` uses (1), which ensures high-quality representation for both rows and columns. This symmetry is a significant advantage of the `HJ-Biplot`, providing a balanced and accurate representation of multivariate data, making it a robust and versatile technique for various types of analyses.

To address the practical implementation of the `HJ-Biplot` technique, it is relevant to mention that its development and application have been supported by the creation of various software tools. These tools have enabled deeper analysis and interactive visualizations, facilitating the interpretation of multivariate data. In this context, Table 2 presents some of the programs and packages specifically developed for the study and application of the `HJ-Biplot`, highlighting their evolution and adaptation to different platforms and research needs. This technological advancement has been key to the dissemination and use of this technique in various fields, allowing researchers to effectively explore and communicate the complex structures present in their data.

Table 2. Software implementing the `HJ-Biplot` technique.

Software	Year	Authors	Platform	Key Innovations
`MultBiplot`	2008	Vicente-Villardón [16]	`R`, `Matlab`	First comprehensive GUI for HJ-Biplot; basic PCA and clustering integration.
`BPCA`	2011	Faria, Allaman, and Demétrio [17]	`R`	Biplots based on principal components; 2D/3D visualization.
`GGEBiplotGUI`	2013	Frutos-Bernal, Galindo, and Leiva [18]	`R`	Specialized for genotype–environment analysis using biplots.
`MultibiplotGUI`	2015	Nieto-Librero, Baccala, Vicente-Galindo, and Galindo [19]	`R`	Multibiplot analysis with bootstrap-based inferential results.
`DynBiplotGUI`	2014	Egido [20]	`R`	GUI for dynamic and classical biplots with 2-way and 3-way matrices.
`TextMiningGUI`	2021	Conrado Reyes and Galindo [21]	`R`	Integration of text mining with HJ-Biplot for semantic analysis.
`PyBiplots`	2021	Torres-Cubilla [22]	`Python`	First Python implementation; compatible with ML workflows.
`SparseBiplots`	2022	Cubilla-Montilla, Torres-Cubilla, Galindo, and Nieto-Librero [23]	`R`	Implements three methods of regularization in each case of the HJ-Biplot: Ridge, LASSO and Elastic Net.

Table 2. *Cont.*

Software	Year	Authors	Platform	Key Innovations
LDABiplots	2022	Pilacuan-Bonete, Galindo, De La Hoz Maestre, and Delgado-Álvarez [24]	R	Web-based GUI to perform Biplots from digital newspapers under the Bayesian approach of Latent Dirichlet Assignment (LDA) and ML algorithms.
Areabiplot	2022	Silva and Freitas [25]	R	Uses NIPALS-based method to estimate data matrix elements visually.
BiplotbootGUI	2023	Nieto-Librero and Freitas [26]	R	GUI to interact with bootstrap methods on classical Biplots and with clustering and/or disjoint Biplot.
MultBiplotR	2023	Vicente-Villardón, Vicente-González, and Frutos-Bernal [27]	R	Package includes classical Biplots, canonical STATIS-ACT, and logistic Biplots, among many others.

As shown in Table 2, various programs and packages have been developed to support the HJ–Biplot technique, providing tools for its implementation and visualization. These include R packages such as BPCA and MultibiplotGUI as well as more recent applications like SparseBiplots and LDABiplots. These programs allow for an in-depth analysis and the generation of interactive graphics that facilitate data interpretation, reflecting the growing importance of the HJ–Biplot in research and professional practice.

Each software tool implementing the HJ–Biplot technique offers unique advantages and limitations, making them suitable for different research contexts. For instance, MultBiplot [16] is widely recognized for its user-friendly interface and robust handling of structured datasets, making it an excellent choice for researchers new to multivariate analysis. However, its performance can be limited when dealing with very large datasets or high-dimensional data. Another relevant software is BPCA (Biplot based on principal components analysis) [17], which allows the creation of 2D and 3D Biplots using the HJ–Biplot method based on principal components. On the other hand, SparseBiplots [23] addresses these limitations by incorporating penalization methods like LASSO and Elastic Net, which are particularly effective for reducing dimensionality and improving interpretability in genomics and big data applications. Despite its advanced capabilities, SparseBiplots requires a deeper understanding of penalization techniques, which may pose a challenge for less experienced users.

Similarly, PyBiplots [22] stands out for its compatibility with Python, which is a programming language widely used in machine learning and data science. This makes it an attractive option for researchers looking to integrate HJ–Biplot analysis into broader machine learning workflows. However, the lack of extensive documentation and community support for PyBiplots can be a drawback for users unfamiliar with Python. Meanwhile, GGEBiplotGUI [18] is specifically designed for agricultural research, offering specialized tools for analyzing genotype-by-environment interactions. While it excels in this niche, its applicability to other fields may be limited. These examples highlight the importance of selecting the right tool based on the specific requirements of the research project, balancing ease of use, functionality, and compatibility with existing workflows.

In this context, the present systematic review and meta-analysis seek to provide a comprehensive synthesis of the studies utilizing the HJ–Biplot technique from its inception in 1986 to December 2024. The sources of these studies include the Scopus and Web of Science databases as well as the repository of master's and doctoral research at the Department of Statistics of the University of Salamanca. This analysis aims to explore the evolution and application of the HJ–Biplot technique in diverse disciplines, identify

the most recurrent areas of application, and evaluate its contribution to data analysis and representation in multivariate scenarios.

To ensure methodological rigor, the PRISMA 2020 framework has been followed, encompassing aspects such as the clear definition of objectives, systematic search of relevant literature, data extraction, and critical appraisal of the included studies. This systematic review aims not only to highlight the theoretical and practical contributions of the HJ-Biplot technique but also to serve as a basis for future research, expanding its applicability and integration with emerging technologies such as artificial intelligence and machine learning.

2. Materials and Methods

The analysis of literature is essential in academic research, as it allows for the identification of trends, knowledge gaps, and emerging areas in a specific field. In this section, we present an innovative methodology to conduct a systematic literature analysis, which is structured into three main components: (1) ***Text Mining Process***, using the IRAMUTEQ software for lexicometric analysis and pattern identification; (2) ***Biplot Analysis***, employing Canonical Biplot techniques to visualize multivariate relationships; and (3) ***Integration of Artificial Intelligence***, leveraging ChatGPT 3.5 to enrich the analysis with AI-generated interpretations and contextual insights. This combined approach not only enables the effective classification and visualization of articles but also enhances the depth and accuracy of the findings. Furthermore, the study adheres to the PRISMA 2020 guidelines, ensuring transparency, rigor, and completeness in the systematic review process.

2.1. Text Mining Process

IRAMUTEQ (Interface de R pour les Analyses Multidimensionnelles de Textes et de Questionnaires) is an open-source software package designed for multidimensional text analysis, supporting various text types including articles, surveys, and legal documents [28]. Unlike commercial alternatives like NVivo [29] or ATLAS.ti [30], IRAMUTEQ specializes in automated lexicometric analysis through natural language processing (NLP) and statistical methods, with particular strengths in Reinert's descending hierarchical classification (DHC) for thematic identification [31,32]. This approach differs from the manual coding emphasis of MAXQDA [33] or the keyword-focused analysis of WordStat [34], offering researchers a unique balance between automated processing and statistical rigor. The software's integration with R provides flexibility for advanced analyses [35,36], although this dependency presents steeper initial setup requirements compared to web-based tools like Voyant [37] or standalone packages like KH Coder [38].

A critical phase in IRAMUTEQ's workflow—and indeed in most text mining processes—involves careful corpus preparation, where UTF-8 formatted texts undergo cleaning and segmentation into Elementary Context Units (ECUs) [39–41]. This preprocessing stage shares similarities with tools like Leximancer [42] and QDA Miner [43], though IRAMUTEQ's automatic text cleaning features provide distinct efficiency advantages for large datasets [44]. The software's analytical capabilities span frequency analysis, specificity examination, and similarity mapping through graph theory [45], which is comparable to functions found in Gensim [46] or MonkeyLearn [47] but with a stronger emphasis on qualitative interpretation. Notably, IRAMUTEQ's DHC implementation offers particular value for uncovering latent thematic structures in extensive text collections [48], which is a feature that complements rather than replaces the manual coding approaches favored in grounded theory research [49].

When evaluating IRAMUTEQ against competing solutions, several tradeoffs emerge. The package excels in automated text processing and statistical integration through R [50],

making it ideal for researchers requiring reproducible, quantitative text analysis. However, its visualization capabilities remain less interactive than NVivo's dynamic graphs [51], and the requirement for R proficiency creates barriers compared to more accessible web tools [52]. These characteristics position IRAMUTEQ as particularly suitable for mixed-methods researchers who value statistical rigor and thematic discovery, while other tools may better serve projects emphasizing qualitative depth [53] or rapid exploratory analysis [54]. The choice between these alternatives ultimately depends on the research objectives, technical capacity, and the specific balance required between automated processing and researcher interpretation in textual analysis [55].

2.2. Biplot Analysis

The Canonical Biplot, or MANOVA-Biplot, is a multivariate statistical technique that combines *multivariate analysis of variance* (MANOVA) with Biplot techniques, allowing for a graphical representation of the data. Introduced by Gabriel (1972, 1995) and further developed by Vicente-Villardón and Galindo, this technique facilitates the visualization of both the differences between groups and the relationships between variables [56].

The MANOVA model for p variables is expressed in matrix form as $\mathbf{X} = \mathbf{AB} + \mathbf{U}$, where $\mathbf{X}$ is the matrix of observations, A is the design matrix, $\mathbf{B}$ is the matrix of unknown parameters, and $\mathbf{U}$ contains the residuals [57]. The general multivariate linear hypothesis is stated as $H_0 : \mathbf{CB} = \mathbf{0}$, where $\mathbf{C}$ is a contrast matrix. Through *Generalized Singular Value Decomposition* (GSVD), the Canonical Biplot is constructed by maximizing the separation between groups [58].

The GSVD is performed as $\mathbf{R}^{-1/2}\hat{\mathbf{D}}\mathbf{E}^{-1/2} = \mathbf{U}\mathbf{D}_\lambda\mathbf{V}^{\mathrm{T}}$, where $\mathbf{R}$ is a contrast matrix, $\mathbf{D}_\lambda$ is the diagonal matrix of eigenvalues, and $\hat{\mathbf{D}} = \mathbf{C}(\mathbf{A}^{\mathrm{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{X}$. The row (observations) and column (variables) markers are calculated as $\mathbf{P} = \mathbf{R}^{-1/2}\mathbf{U}\mathbf{D}_\lambda$ and $\mathbf{Q} = \mathbf{E}^{-1/2}\mathbf{V}$, respectively, allowing for the Biplot representation of the original data. This graphical representation facilitates the interpretation of relationships between observations and variables in a reduced space. Rows reflect the similarity between observations, while columns indicate the relationships between variables [59]. Additionally, *confidence regions* around the points representing group means can be added through confidence circles, providing an intuitive visualization of the uncertainty in the observed differences between groups.

In the Canonical Biplot shown in Figure 3, each point represents a keyword extracted through our text mining process using IRAMUTEQ software with colors indicating their thematic group membership or their study year groups. The larger points denote cluster centroids, which are surrounded by confidence circles that visualize the variability within each lexical group. The vectors in this visualization correspond to the document IDs from our study corpus, where their direction and magnitude reveal the relationship between specific articles and the extracted keywords. Notably, longer vectors indicate documents that contribute more significantly to the differentiation of word clusters, serving as important markers of thematic influence in our analysis. This representation proves particularly valuable for examining the complex relationships between textual patterns (represented by keywords) and their distribution across our research documents, providing a comprehensive view of the semantic structure emerging from our multivariate text analysis.

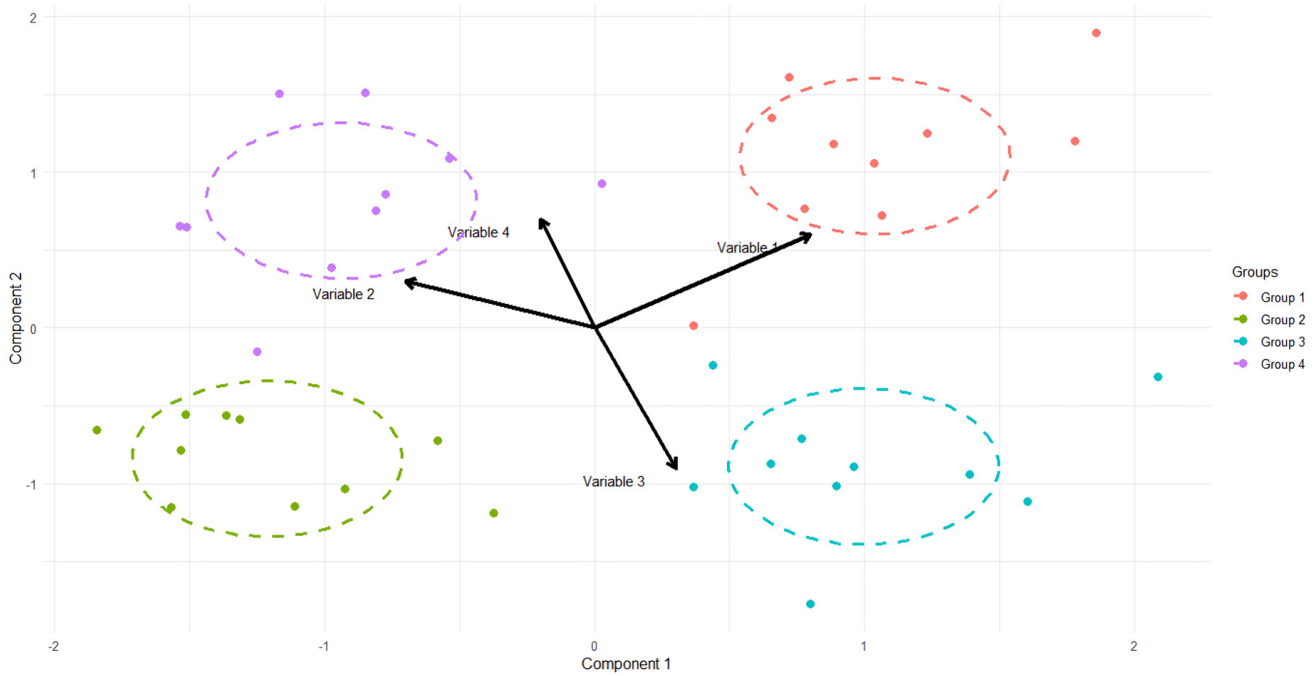


Figure 3. `Canonical Biplot` with confidence circles and differentiated groups.

2.3. Integration of Artificial Intelligence

`ChatGPT`, developed by `OpenAI`, represents a significant advancement in generative language models through its Transformer architecture, which utilizes multi-head attention mechanisms to process complex textual relationships and generate coherent responses [60]. Evolving from `GPT-1` (2018) to `ChatGPT 3.5` and `GPT-4` (2022–2023), these models leverage supervised learning and fine tuning on extensive text corpora, enabling versatile applications from translation to content generation [61]. While `ChatGPT 3.5` remains widely accessible, its underlying improvements in efficiency and output quality have solidified its role in natural language processing [62–64].

Beyond standalone applications, `ChatGPT` enhances traditional text-mining methods by providing contextual interpretations, summarization, and trend identification for large datasets [65]. Its prompt-based generation capabilities complement analytical tools like `IRAMUTEQ`, offering researchers deeper insights into textual patterns and supporting more nuanced decision making [66]. However, effective integration requires balancing these AI-driven advantages with rigorous validation to ensure accuracy and mitigate the potential biases inherent in generative models [67].

3. A New Seven-Phase Methodology for Systematic Literature Review

3.1. ***Phase 1:*** *Article Screening*

In this initial phase, we present the results of an extensive textual analysis of 121 articles on the `HJ-Biplot` technique by Galindo, obtained from a search in the Web of Science (WOS) and Scopus databases, which yielded 204 initial results. This was conducted using the following search equation: *"HJ-Biplot" OR "HJ Biplot" OR "HJBiplot" OR "HJ biplot" OR "HJ-biplot" OR "GH-Biplot" OR "JK-Biplot" OR "GH Biplot" OR "JK Biplot" OR "GH biplot" OR "JK biplot" OR "GHbiplot" OR "JKbiplot"*, covering variants and related techniques. As shown in Figure 4, after applying the `PRISMA 2020` protocol to assess the relevance and quality of the articles [68], 12 were excluded for incomplete information. Subsequently, 78 duplicate articles were removed, resulting in a base of 114 articles: 83 from WOS and 31 from Scopus.

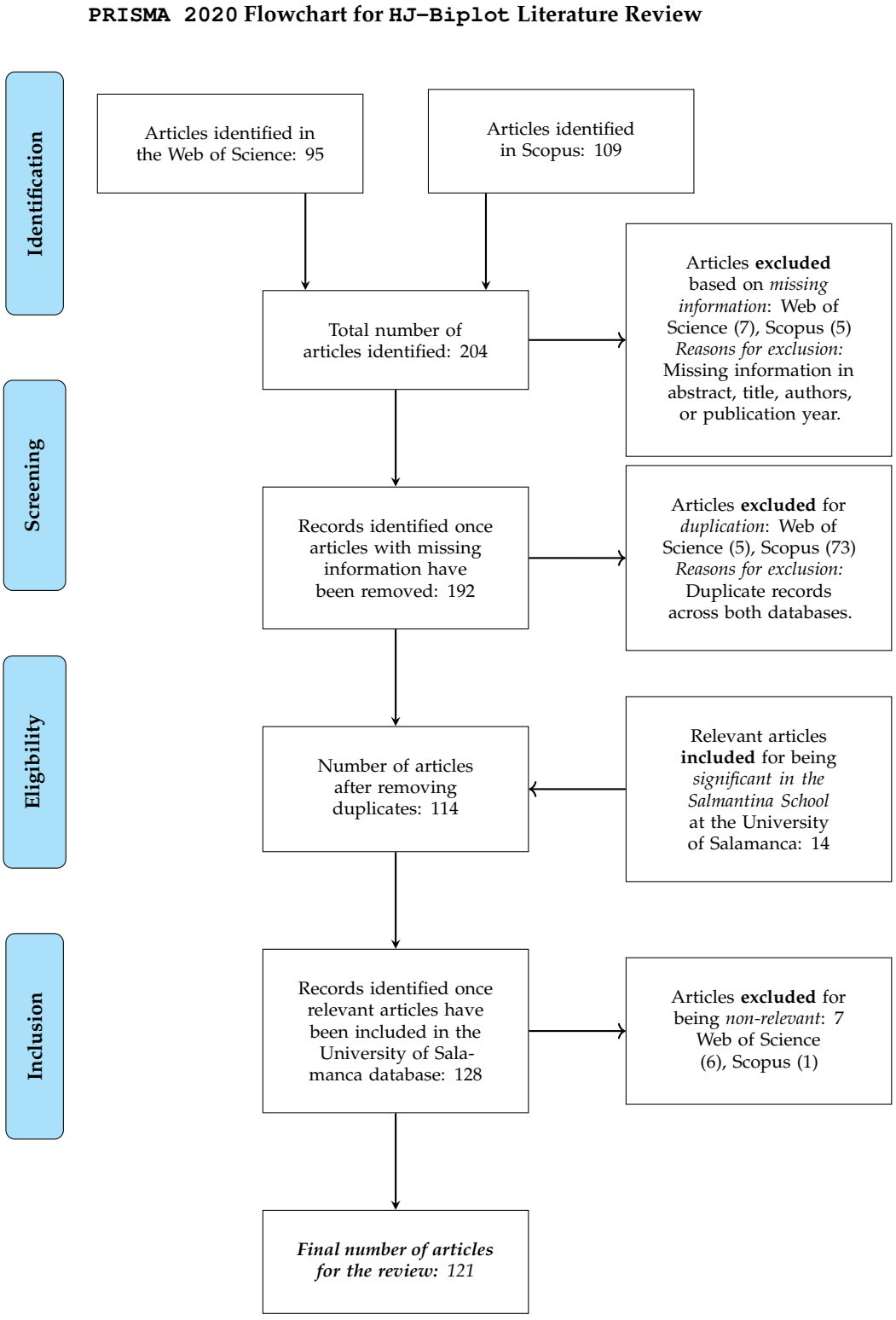


Figure 4. Flowchart of the literature selection process according to the PRISMA 2020 guidelines for articles related to the HJ-Biplot technique.

In addition to the initial search in WOS and Scopus, further research was conducted using the University of Salamanca databases. This step allowed the inclusion of 14 additional articles that were not captured by the WOS or Scopus search engines. Among these, the inclusion of Galindo's seminal 1986 article, a key study for the development of the HJ-Biplot technique, stood out. With this addition, the total number of articles considered rose to 128.

In the final screening phase, an evaluation of the eligibility of the articles was carried out to ensure that they met the established inclusion criteria. During this review, it was identified that 6 articles from WOS and 1 article from Scopus did not meet the quality or relevance criteria, leading to their exclusion. As a result, 77 articles from WOS, 30 from Scopus, and 14 additional articles not captured by the search engines were selected, giving a final total of 121 articles for analysis.

Figure 5 represents a co-occurrence analysis of terms related to the use of the `HJ-Biplot` and its applications in various research areas. The larger nodes, such as "hj-biplot", "multivariate analysis", and "human", indicate central terms that have been frequently mentioned together in the analyzed texts, suggesting their relevance in the literature. The colors differentiate thematic groups; for example, the green group is associated with sustainability and sustainable development topics, while the red group is related to risk factors and gender violence. Terms such as "sustainability", "corporate social responsibility", and "cluster analysis" also highlight its application in ecological, business, and social studies. The connections between the nodes suggest how these themes are interrelated, reflecting a multidisciplinary evolution of the `HJ-Biplot` in diverse fields such as health, the environment, and social sciences.

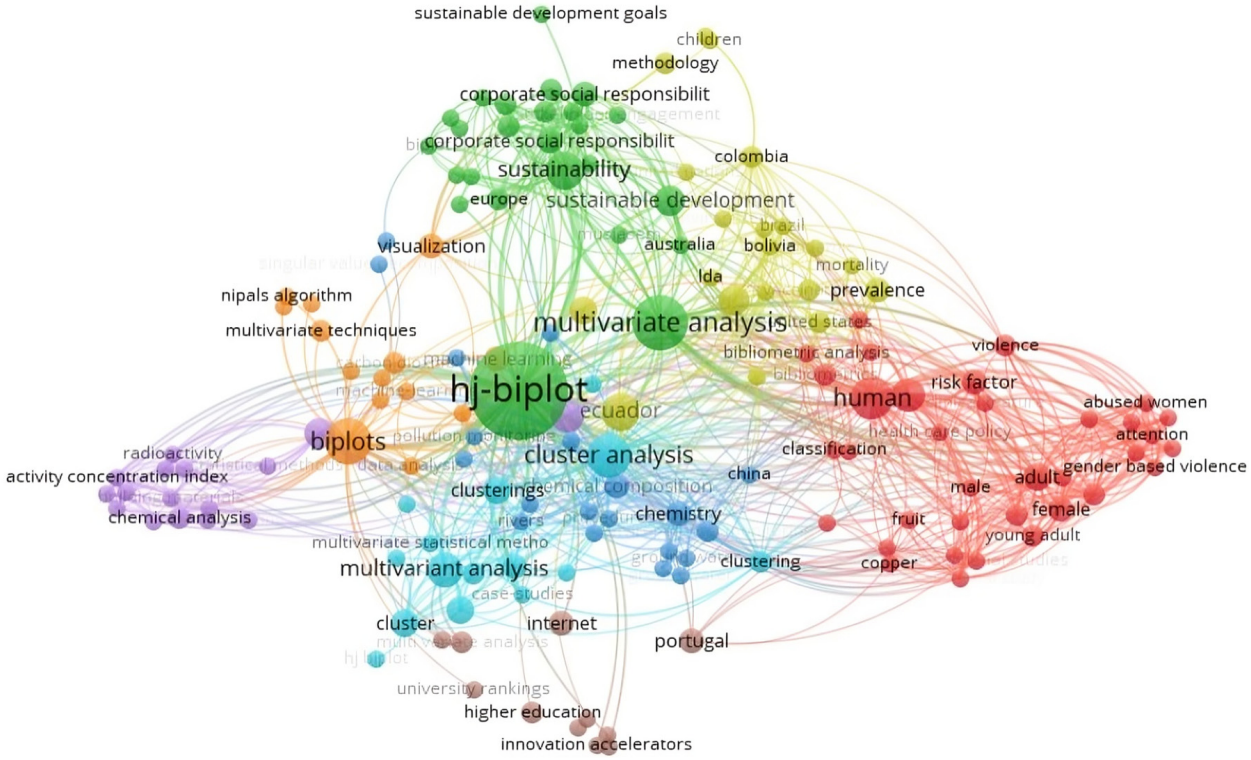


Figure 5. Word cloud and their interconnections in the study articles.

3.2. ***Phase 2:*** *Data Preparation*

Once the eligible articles were obtained, they were coded for processing in the `IRAMUTEQ` software, as shown in Figure 6. For the coding, an additional column was added to the `Excel` file containing the articles, where a specific code was inserted that concatenated an article identifier with its abstract. This code was designed to be placed later in a plain text file in *UTF-8* format, which would serve as the corpus for processing by `IRAMUTEQ`.

The coding process followed the standards specified by `IRAMUTEQ`, including the insertion of four asterisks to indicate variables and modalities. This structure in `Excel` not only organized the data systematically but also ensured that each article was correctly

identified and prepared for analysis in the software. The format used in the coding is essential for IRAMUTEQ to properly recognize the variables and modalities of each text, allowing for efficient and accurate analysis of the *textual corpus*.

	A	B	C	D	E	F	G	H
1	id	authors	title	year	abstracts	data		
2	1	GALINDO M. P.	An alternative for Simultaneous represe	1986	In the present work, a review of the BIPLOT	**** *ID_1@In the present work, a review of the BIPLOT		
3	2	ORFAO	Clinical and Immunological Findings ir	1988	In order to define the characteristics of B-(	**** *ID_2@In order to define the characteristics of B-C		
4	3	E. GALANTE	Comparison of Spatial Distribution Patt	1991	The seasonal and spatial distributions o	**** *ID_3@The seasonal and spatial distributions of (		
5	4	SANTOS, C; MUN	CHARACTERIZATION OF YOUNG RED WI	1991	The anthocyanin contents of 48 young red	**** *ID_4@The anthocyanin contents of 48 young red '		
6	5	RIVASGONZALO,	BIPLOT ANALYSIS APPLIED TO ENOLOGI(	1993	Fifteen variables including conventional e	**** *ID_5@Fifteen variables including conventional er		
7	6	MEDER, MDO; G(	DIFFERENTIATION OF GRAPES ACCORDI	1994	The anthocyanin composition of the skins	**** *ID_6@The anthocyanin composition of the skins		
8	7	GALINDO M. P.	Estudio comparativo de ordenación d	1996	In this work we attemp to analyse how ir	**** *ID_7@In this work we attemp to analyse how imp		
9	8	GALINDO M. P.	EL ANALISIS HJ-BIPLOT COMO HERRAMII	1999	The aim of this work is to show the use of	**** *ID_8@The aim of this work is to show the use of h		
10	9	Garcia-Talegon,	Determination of the origin and evoluti(	1999	The aim of the present work is to determin	**** *ID_9@The aim of the present work is to determine		
11	10	Alarcón, Paula;	Estilos de Personalidad y Desadaptaci(	2005	The present study was aimed at identifyin(	**** *ID_10@The present study was aimed at identifyin		
12	11	Iñigo, AC; López	Monitoring of origin and evolution of bu	2005	The aim of this work is to establish the ori	**** *ID_11@The aim of this work is to establish the or		
13	12	Cabrera, JMG; M	Study of the evolution of air pollution in	2006	Five-year data of SO2, PM10, NO, NO2, O-(	**** *ID_12@Five-year data of SO2, PM10, NO, NO2, O-		
14	13	Alcantara, Manu	The spatial dimensions of left-right pol	2007	This article uses the interview data from th	**** *ID_13@This article uses the interview data from t		
15	14	GALINDO M. P.	Caracterización Multivariante de los pe	2007	The objective of this work is identifying the	**** *ID_14@The objective of this work is identifying th		
16	15	Celestino Sanch	Socio-economic profile of women micr	2008	To evaluate the situation of the Micro busi	**** *ID_15@To evaluate the situation of the Micro bus		
17	16	CASTELA E	ECOLOGICAL INFERENCE FOR THE CHAR	2009	Ecological Inference (IE) is a set of statis	**** *ID_16@Ecological Inference (IE) is a set of statist		
18	17	MENDEZ S	The study of bacterioplankton dynamic	2009	The relationship between bacterioplank	**** *ID_17@The relationship between bacterioplankto		
19	18	MARREIROS A	THE PATHOLOGICAL-NUMERIC COD	2010	The information stated by Public Hospit	**** *ID_18@The information stated by Public Hospital		
20	19	Serafim, A.; Con	ASSESSMENT OF ESSENTIAL AND NONES	2012	The general population is exposed to met	**** *ID_19@The general population is exposed to met		
21	20	Diaz-Faes, Adria	HJ-Biplot as a tool for inspection of bib	2013	The aim of this paper is to demonstrate th	**** *ID_20@The aim of this paper is to demonstrate th		

Figure 6. Coding of identifiers and abstracts of the first 20 articles.

3.3. ***Phase 3:*** *Data Loading and Processing with the IRAMUTEQ Software*

Once the articles were coded and stored in a plain text file, the corpus was loaded into IRAMUTEQ for analysis. The corpus must meet specific structural criteria, including *UTF-8* encoding, text segmentation, and the selection of dictionaries and lemmatization options. Lemmatization is crucial for standardizing linguistic forms, transforming verbs into their infinitive form, nouns into singular, and adjectives into masculine, thus facilitating the detection of patterns and relationships in the texts. This process ensures that the analysis is carried out consistently and accurately, providing a faithful representation of the content of the articles.

After configuring and validating the corpus, the text indexing process was initiated, which can take several minutes depending on the size of the corpus. This process is essential for preparing the corpus for the various analyses that IRAMUTEQ offers, such as textual statistics, similarity analysis, hierarchical classification, and the generation of word clouds. Proper coding and preparation of the corpus are crucial to obtaining representative and accurate results, allowing valuable conclusions to be drawn about Galindo's HJ-Biplot technique from the selected articles.

With the validated corpus, correspondence factor analysis (CFA) was performed. CFA allows for the exploration of relationships between rows and columns in a contingency table. In our study, correspondence factor analysis (CFA) was applied to identify co-occurrence patterns among the words used in the abstracts of articles about the HJ-Biplot. This analysis helps visualize clusters of frequently occurring terms and their proximity to certain articles, making it easier to understand how certain concepts are interrelated in the literature on this technique.

CFA also detects specificities within the corpus, identifying terms characteristic of certain subgroups. This is particularly useful when analyzing texts from different eras or research areas, as it allows us to observe how certain terms or topics are associated with specific contexts. Upon completing the CFA, as seen in Figure 7, a *lexical matrix* is obtained that represents the frequencies of key terms in each article, revealing important patterns in the corpus and providing a detailed view of the evolution and distribution of topics related to the HJ-Biplot.

	Column1	*ID_1	*ID_10	*ID_100	*ID_101	*ID_102	*ID_103	*ID_104	*ID_105	*ID_106	*ID_107	*ID_108	*ID_109	*ID_11
2	dynamic	0	0	0	0	1	0	0	0	0	0	0	0	0
3	risk	0	0	0	0	0	0	0	0	0	0	0	0	0
4	affect	0	0	0	2	0	0	1	0	0	0	0	0	0
5	cenethjbiplot	0	0	0	0	0	10	0	0	0	0	0	0	0
6	net	0	0	0	0	0	1	0	0	0	0	0	0	0
7	interpret	0	0	0	0	0	1	0	1	0	1	0	0	0
8	study	0	1	1	1	2	1	1	2	0	5	1	0	1
9	total	0	0	0	0	0	0	0	0	0	1	0	0	0
10	program	0	0	0	0	0	0	0	0	0	0	0	0	0
11	call	1	0	0	0	0	1	0	0	0	0	0	0	0
12	type	0	5	0	0	2	0	0	0	0	0	0	0	3
13	work	1	1	0	1	0	1	0	2	0	1	0	0	1
14	end	0	0	0	0	0	0	0	0	0	0	1	0	0
15	provide	0	0	0	0	0	1	0	0	0	0	0	0	0
16	methodology	0	0	1	0	1	1	0	0	0	0	0	0	0
17	correlation	0	0	1	2	1	0	0	0	0	0	0	0	0
18	operate	0	0	0	0	0	0	0	0	1	0	0	0	0
19	order	1	0	0	0	0	0	0	0	0	0	0	1	0
20	interpretation	0	0	0	0	0	1	0	0	0	0	0	0	0
21	cll	0	0	0	0	0	0	0	0	0	0	0	0	0
22	series	0	0	0	0	0	0	0	0	0	0	0	0	0

tableafcm

Figure 7. Lexical matrix obtained from the CFA with the IRAMUTEQ (Version 0.7 alpha 2) software.

3.4. ***Phase 4:*** *Characterization of the Lexical Matrix with the R Software*

The obtained lexical matrix consists of 265 variables (words) and 121 individuals (article identifiers), resulting in a size of 266 × 122. This matrix was saved in CSV format. For the creation of the Canonical Biplot, it is necessary to transpose the matrix and apply a *characterization factor*, as suggested in [69]. This factor is calculated using the following formula:

$$\mathbf{f}_{\mathbf{ij}}^{*} = \frac{\mathbf{f}_{\mathbf{ij}}}{\sqrt{\max(\mathbf{f}_{\mathbf{i}})}\sqrt{\max(\mathbf{f}_{\mathbf{j}})}}$$

which adjusts the matrix values based on the maximum of each row *i* and column *j*, allowing for proper characterization of the data. The process is carried out in the R software *version 4.4.1* [70], starting with the transposition of the matrix, which is followed by applying the formula to adjust the values. These partial results are shown in Figure 8. Finally, the results are saved in an Excel file, ensuring the correct association between the article identifiers and their corresponding data. This procedure optimizes the data matrix for the Canonical Biplot analysis, ensuring accurate visualization and meaningful interpretation.

	ID	dynamic	risk	affect	cenethjbiplot	net	interpret	study	total	program	call	type	work
2	*ID_1	0	0	0	0	0	0	0	0	0	0.196116	0	0.160128
3	*ID_10	0	0	0	0	0	0	0.182574	0	0	0	1	0.258198
4	*ID_100	0	0	0	0	0	0	0.182574	0	0	0	0	0
5	*ID_101	0	0	0.377964	0	0	0	0.154303	0	0	0	0	0.218217
6	*ID_102	0.182574	0	0	0	0	0	0.333333	0	0	0	0.365148	0
7	*ID_103	0	0	0	1	0.119522	0.223606	0.129099	0	0	0.223606	0	0.182574
8	*ID_104	0	0	0.288675	0	0	0	0.235702	0	0	0	0	0
9	*ID_105	0	0	0	0	0	0.316227	0.365148	0	0	0	0	0.516397
10	*ID_106	0	0	0	0	0	0	0	0	0	0	0	0
11	*ID_107	0	0	0	0	0	0.316227	0.912870	0.223606	0	0	0	0.258198
12	*ID_108	0	0	0	0	0	0	0.288675	0	0	0	0	0
13	*ID_109	0	0	0	0	0	0	0	0	0	0	0	0
14	*ID_11	0	0	0	0	0	0	0.166666	0	0	0	0.547722	0.235702
15	*ID_110	0	0	0.188982	0	0	0	0.308606	0.188982	0	0	0	0
16	*ID_111	0.182574	0	0	0	0	0	0.333333	0.408248	0	0	0.182574	0
17	*ID_112	0	0.666666	0	0	0	0	0.471404	0	0	0	0.258198	0
18	*ID_113	0	0	0.250000	0	0	0.353553	0.408248	0.250000	0	0	0	0.288675
19	*ID_114	0	0	0	0	0	0	0	0	0	0	0	0.258198
20	*ID_115	0	0	0	0	0	0	0.166666	0	0.288675	0	0	0.235702

Figure 8. Processed data matrix with the characterization factor.

3.5. ***Phase 5:*** *One-Way Canonical Biplot Analysis with the MultBiplot Software*

Based on the characterized matrix, an additional column with the publication year of each article and another column labeled "group" were added. In this latter column, four publication period groups were established, which were distributed as follows: *Group 1*

(1986–1999), *Group 2 (2000–2007)*, *Group 3 (2008–2015)*, and *Group 4 (2016–2024)*. These groups are essential for performing the one-way `Canonical Biplot` analysis, as they allow segmenting publications according to the mentioned periods. The data were then loaded into the `MultBiplot` *version 18.0312* software [16], developed at the University of Salamanca by the Applied Multivariate Analysis research group, to conduct the corresponding `MANOVA-Biplot`, which will allow us to analyze the variability between the groups and associations with the lexical variables in the different periods.

As shown in Table 3, the result of the `Canonical Biplot` shows the main dimensions, their eigenvalues, and the variance explained by each of these dimensions. In this case, the first dimension has an eigenvalue of 16.07, explaining 48.39% of the total variance of the model. The second dimension has an eigenvalue of 13.04, explaining 31.85% of the variance, while the third dimension, with an eigenvalue of 10.27, explains the remaining 19.76% of the variance.

Table 3. Explained and cumulative variance of the `Canonical Biplot` analysis.

Dimension	Eigenvalue	% Explained Variance	% Cumulative Explained Variance
1	16.07	48.39	48.39
2	13.04	31.85	80.24
3	10.27	19.76	100

Another important result is the *quality of the representation* of group means on the *canonical axes*. Table 4 shows how the different publication periods are projected onto the two main axes of the analysis. We observe that Group 4 (2016–2024) is very well represented, with a value of 877 on Axis 1 and 104 on Axis 2, yielding a cumulative value of 981. This indicates that most of the variability of this group is captured in the first axis, with a fairly high representation also in the second axis, suggesting that this group has a strong presence in the analyzed dimensions.

Table 4. Quality of representation of group means $\times$ 1000.

Group No.	Period	Axis 1	Axis 2	Cumulative
1	1986–1999	730	97	827
2	2000–2007	227	251	478
3	2008–2015	208	767	975
4	2016–2024	877	104	981

On the other hand, Group 2 (2000–2007) shows the lowest representation, with a value of 227 on Axis 1 and 251 on Axis 2, accumulating a total of 478. This low cumulative value indicates that this group is not well represented on the main axes of the `Biplot`, suggesting that the characteristics of this period do not align as clearly with the primary directions of variability in the data. In contrast, Group 1 (1986–1999) and Group 3 (2008–2015) show more balanced representations, with cumulative values of 827 and 975, respectively, highlighting that these groups have a good projection on at least one of the main axes, although each shows different focal points of representation with Group 1 better represented on Axis 1 and Group 3 on Axis 2.

The `Canonical Biplot` graph in Figure 9 shows that Axis 1 explains 48.39% of the variance, and Axis 2 explains 31.85%, meaning that together they represent 80.24% of the variability in the data. The publication period groups are distributed according to techniques derived from the `HJ-Biplot` [12]. The period 2016–2024 is associated with more recent techniques, such as `Cenet HJ-Biplot` [71] and `Sparse HJ-Biplot` [72], indicating a diversification in the development of these techniques. In contrast, the period

1986–1999 reflects the beginning of the HJ-Biplot, primarily associated with its original version, while the period 2008–2015 is linked to techniques such as the Bootstrapping HJ-Biplot [73] and Dynamic Biplot [74], suggesting an interest in adding robustness and dynamism to the analysis.

In addition to the technical evolution, the Biplot also reveals how the applications of the HJ-Biplot have changed over different periods. The period 2016–2024 shows a strong relationship with contemporary topics such as the impact of COVID-19, food security, and environmental issues with a significant geographical focus on Latin America. On the other hand, the period 2008–2015 is associated with terms such as sustainability, agriculture, and water resources, indicating the use of these techniques to address global sustainability issues. The period 1986–1999 shows a more academic focus with applications of the HJ-Biplot in survival studies and university environments.

The period 2000–2007 is linked to terms such as crime, pollution, and gender issues, suggesting that during this stage, HJ-Biplot-derived techniques began to be applied in social and environmental studies, addressing humanitarian and social issues. This marks a transition toward greater diversification in the applications of the technique, expanding to socially relevant topics and covering a broader spectrum of contemporary issues.

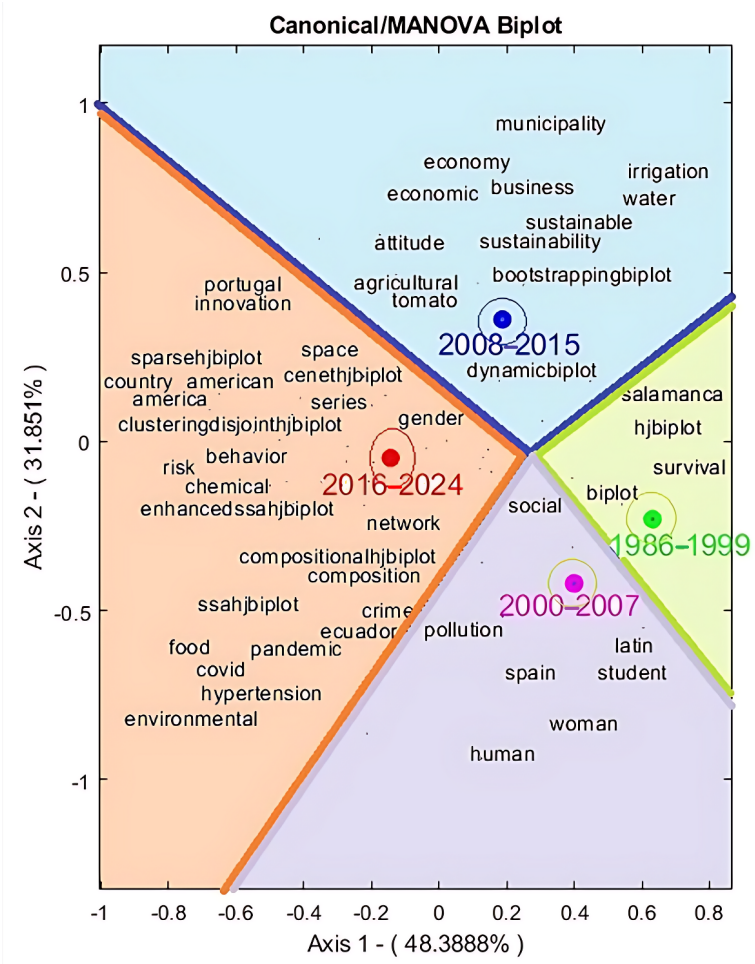


Figure 9. Complete one-way Canonical Biplot.

Although the Canonical Biplot has proven to be a useful tool for visualizing the evolution and applications of the HJ-Biplot over time, its ability to interpret words frequently can be limited. This is where *artificial intelligence*, such as ChatGPT, comes into play by providing a deeper contextual analysis, allowing for the better interpretation of the words and topics within the texts. By complementing the Biplot results with the

capabilities of ChatGPT, a clearer and more precise understanding of the relationships and patterns present in the texts is achieved, significantly enriching the textual analysis.

3.6. ***Phase 6:*** *Use of ChatGPT 3.5 Artificial Intelligence for Textual Analysis*

To add an additional layer of information to the systematic literature review on the HJ-Biplot, artificial intelligence, specifically ChatGPT 3.5, was employed as a powerful and complementary tool. This tool not only enables the analysis of large volumes of text but also contextualizes and extracts relevant patterns that may not be evident through traditional text mining methods. The goal was to use ChatGPT to process the abstracts of articles from each previously defined study period, extracting the most relevant information in chronological order and focusing on identifying key articles, derivative techniques of the HJ-Biplot, and the applications and evolution of these studies.

To carry out this process, specific prompts were designed in ChatGPT 3.5, as shown in Table 5. These prompts aimed to extract chronological information, identify seminal articles, and analyze the evolution and applications of the HJ-Biplot. This integrative approach provided an additional layer of analysis, enriching the understanding of the data collected through the Canonical Biplot.

Table 5. Prompts executed in ChatGPT 3.5 for textual analysis.

Prompt Objective	Prompt	Prompt Explanation
Extract chronological information	Analyze the following summaries and extract the most relevant information in chronological order. Identify key events, methodological advances, and any significant changes in the application of the HJ-Biplot technique.	This prompt organizes the information from the summaries in chronological order, highlighting important milestones in the development of the HJ-Biplot.
Identify key articles	Given the following summaries of articles, identify whether this work is a key or seminal article in the development of the HJ-Biplot or its derivative techniques. Justify why it could be considered a key work.	This prompt helps detect the most influential articles in the evolution of the HJ-Biplot.
Extract applications and evolution	Review the following article summaries and extract the most important applications of the HJ-Biplot. Additionally, identify how the use of this technique has evolved in the field of study over the analyzed period.	This prompt highlights the areas of application of the HJ-Biplot and its evolution over time.

By inputting the article summaries from each period along with these prompts, ChatGPT 3.5 provided an additional layer of analysis, enabling not only a clearer synthesis of findings but also the identification of trends and evolutionary patterns. This facilitated the understanding of how the HJ-Biplot has been adapted and applied in different contexts and how research on this technique has progressed over time. The information extracted by ChatGPT 3.5 was carefully *cross-referenced* with the data obtained through the Canonical Biplot, ensuring that the derived conclusions were both accurate and comprehensive.

After executing these prompts in ChatGPT 3.5 and loading the articles in groups of 10 with their publication year, authors, title, and abstract, a comprehensive set of results was generated. These results, which include key findings, chronological trends, and the evolution of HJ-Biplot applications, are summarized in Table 6. This table provides a detailed overview of the most relevant insights extracted by ChatGPT 3.5, which were organized by year and highlighting significant milestones in the development and application of the HJ-Biplot technique. The information represents a critical component of the analysis, offering a structured and accessible synthesis of the *AI-generated data*.

Table 6. Some results obtained from the execution of prompts with `ChatGPT 3.5`.

Year	**`ChatGPT 3.5` Key Findings**
1986	The `HJ-Biplot` was introduced by Galindo as an improvement to Gabriel's `Biplot` method, allowing for a more precise simultaneous representation of data matrices.
1991	Applied by Santos et al. to analyze anthocyanin profiles in young wines, demonstrating its utility in classification and discrimination in applied sciences.
1993	Used by Rivas et al. in enology to geographically classify young wines from Ribera de Duero and Toro based on enological and phenolic parameters.
1994	Applied by Meder et al. to differentiate grape varieties based on the composition of anthocyanins in the skin, highlighting its potential in agricultural product classification.
1996	Positioned by Galindo as an effective technique in the analysis of ecological communities in a comparative study of multivariate techniques.
1999	Applied by Galindo to study aquatic ecosystems, emphasizing the importance of derived indices for proper interpretation. Garcia-Talegon et al. used it to determine the origin and evolution of building stones, extending its application to geology and historical monument conservation.
2005	Used by Alarcón, Vinet, and Salvo to identify five personality profiles in adolescent offenders in Chile, suggesting these profiles could predict the recurrence and severity of crimes.
2007	Applied by Alcantara and Rivas to study political polarization in Latin America, identifying the main dimensions dividing left and right political parties.
2010	Used by Marreiros to group public hospitals in Portugal based on the quality of their clinical records and their relationship with funding, identifying five key hospital groups for management and evaluation.
2013	Demonstrated by Diaz-Faes et al. in bibliometric studies to identify patterns of scientific production in CSIC centers. Martinez-Ferrero and Gallego-Alvarez used it to analyze variations in CO_2 emissions from international companies, revealing significant differences between geographic regions.
2015	Expanded into sustainability, innovation, and public health studies. Delgado Álvarez and Galindo proposed an innovative approach for the spatiotemporal analysis of traffic matrices, highlighting the superiority of the `HJ-Biplot` over PCA.
2017	Applied in journalism by Alende Castro and García González to visualize trends in Preventive Journalism discourse. Amor Esteban et al. used it to study the influence of cultural values on corporate social responsibility practices in 18 countries.
2019	Used by Carrasco et al. to evaluate water quality in Gamboa and Paraíso, identifying clusters of sampling points correlated with the seasons. González-García et al. applied it to identify four types of students based on their attitudes and learning approaches in general didactics.
2020	Applied by Ascencio Jordán et al. to study innovative behavior in Ecuadorian universities, revealing how students' innovative characteristics vary by university type and educational context.
2021	Introduced advanced techniques like the `Sparse HJ-Biplot` by Cubilla-Montilla et al., combining the `HJ-Biplot` with Elastic Net to handle large datasets. Martinez-Regalado et al. applied `HJ-Biplot` and `External Logistic Biplot` in CSR, demonstrating its effectiveness in sustainability analysis.
2022	Used by Tenesaca-Chillogallo and Amaro to analyze the relationship between COVID-19 and other health conditions, identifying significant correlations with diseases such as hypertension and diabetes. Cornejo et al. applied it to analyze pension indicators in Latin America, highlighting the impact of the economic crisis and the pandemic.
2023	Applied by Cano et al. to determine the Activity Concentration Index (ACI) in construction materials, offering an alternative to gamma spectrometry. Crespo et al. used it to analyze the relationship between crime, poverty, and unemployment in Ecuador.
2024	Used by Almorza et al. to classify ports and ships under the Paris Memorandum of Understanding, improving maritime safety indicators. Duran-Ospina et al. conducted a bibliometric study on keratomycosis, emphasizing the need for new therapies.

The integration of ChatGPT 3.5 into the systematic literature review on the HJ-Biplot proved to be a transformative approach, enabling a deeper and more nuanced understanding of the technique's evolution and applications. By leveraging AI-generated insights, this study not only identified key trends and seminal works but also uncovered patterns that traditional methods might have overlooked. The results presented in Table 6 represent only a portion of the extensive information extracted by ChatGPT 3.5, which includes detailed chronological analyses, key article identification, and the evolution of HJ-Biplot applications across various fields. However, these AI-generated insights must be carefully cross-referenced with the findings from the Canonical Biplot and text mining analyses, which were conducted as preliminary steps in this study. This triangulation of methods ensures the robustness and reliability of the conclusions, as it combines the strengths of AI-driven textual analysis with the precision of multivariate visualization and the depth of lexicometric exploration. This innovative methodology underscores the potential of combining advanced AI tools with traditional analytical techniques to enhance research outcomes, paving the way for future interdisciplinary studies that can address complex, multidimensional problems with greater precision and insight.

3.7. ***Phase 7:*** *Consolidation of Information and Creation of the Timeline of the HJ-Biplot Technique Development*

The HJ-Biplot, introduced by Galindo in 1986, was a significant advancement in multivariate analysis, enabling the simultaneous representation of data matrices with superior fitting for both rows and columns in the same reference system [12]. Following its introduction, the technique was applied in various fields. Orfao in [75] used it to define characteristics of large lymphocyte populations in B-CLL cases. In 1991, Galante explored the spatial distribution of dung-feeding scarabs in Mediterranean pasturelands [76], while Santos et al. differentiated young wines by anthocyanin profiles, showcasing the method's ability for classification and discrimination [77]. Rivas et al. (1993) expanded its use to classify wines geographically based on phenolic and chemical variables [78]. Additionally, Meder et al. (1994) applied the HJ-Biplot to distinguish grape varieties by anthocyanin composition, demonstrating its robustness in agricultural and food sciences [79].

In 1996, Galindo advanced the application of the HJ-Biplot with his study *"Comparative Study of the Ordering of Ecological Communities Based on Factorial Techniques"* [80], demonstrating its effectiveness in analyzing ecological communities compared to other multivariate techniques. In 1999, Galindo applied the method to aquatic ecosystems in *"HJ-Biplot analysis as a tool for studying an aquatic ecosystem"* [81], emphasizing its utility in interpreting ecosystem indices, while Garcia-Talegon et al. extended its use to geology, analyzing the origin and evolution of building stones based on chemical composition [82]. The versatility of the HJ-Biplot was further showcased in 2005 when Alarcón et al. identified personality clusters among Chilean adolescents in *"Personality Styles and Social Maladaptation During Adolescence"* [83], and Iñigo et al. monitored the geological evolution of building stones through chemical analysis [84].

In 2006, Cabrera et al. employed the technique to study air pollution in Salamanca over a five-year period, capturing pollutant relationships and temporal evolution [85], while in 2007, Alcantara and Rivas analyzed political polarization in Latin America using the HJ-Biplot to reveal ideological dimensions [86], and Galindo examined socioeconomic profiles of women in undeclared employment in Salamanca [87]. In 2008, Celestino and Gonzalez applied the HJ-Biplot to identify socioeconomic profiles of female micro-entrepreneurs in Mexico, combining it with cluster analysis for regional insights [88], and in 2009, Castela used the method to analyze electoral turnout patterns in Portugal, while Mendez explored bacterioplankton dynamics in the Berlengas Archipelago, showcasing the method's adaptability to diverse scientific fields [89,90].

In 2010, Marreiros utilized the `HJ-Biplot` to classify public hospitals in Portugal based on clinical record quality and funding relationships [91]. By 2012, Serafim et al. applied it to assess environmental contamination risks in mothers from southern Portugal by analyzing placental biomarkers [92]. In 2013, the method proved versatile in bibliometric studies, analyzing greenhouse gas emissions in international companies and grouping them by geographical regions, as demonstrated by Diaz-Faes et al., Martinez-Ferrero, and Gallego-Alvarez [93,94]. That same year, Torres-Salinas et al. highlighted its use in bibliometric and scientific indicator analyses [95]. In 2014, Felicio examined the connection between governance mechanisms and the performance of publicly traded companies, while Gallego-Alvarez et al. applied the `HJ-Biplot` to study corporate social responsibility in Brazilian firms and the environmental performance of 149 countries, identifying socioeconomic and institutional factors as key determinants [96–98].

In 2014, the `HJ-Biplot` was applied to diverse areas: Hernandez et al. studied the impact of agricultural techniques and harvesting periods on tomato quality [99]; Herrera Ramírez et al. evaluated the nutritional requirements of tropical tree species for urban forestry [100]; and Caballero et al. integrated qualitative and quantitative methods to analyze focus group discussions, offering a novel mathematical characterization of discourse [69]. Additionally, Morillo et al. assessed the performance of research networking centers in psychiatry and gastroenterology [101]. By 2015, Delgado and Galindo introduced a spatiotemporal traffic matrix analysis method using `HJ-Biplot`, demonstrating improved temporal and spatial correlation representation over PCA [102], while Egido proposed the `Dynamic Biplot` to analyze economic freedom evolution in the EU, identifying greater freedom in non-eurozone countries [74]. Ferreira et al. explored soil erodibility variations influenced by land use [103], and Gallego-Alvarez et al. analyzed global Sustainable Society Index disparities, correlating them with geographical differences [104].

In 2015, the `HJ-Biplot` advanced with the introduction of the `Bootstrap HJ-Biplot` by Nieto-Librero, incorporating bootstrap confidence intervals and validation through simulated and real data [73], and its application by Ortas et al. in analyzing sustainability performance across companies in various countries [105]. That same year, Patino-Alonso et al. identified lifestyle clusters linked to cardio-metabolic health [106], while in 2016, Cadavid-Ruiz et al. used the technique to study executive function in children [107], and Suarez et al. explored bioactive compounds in tomatoes with the innovative `Compositional HJ-Biplot` [108]. By 2017, applications expanded further: Alende and García employed the `HJ-Biplot` for analyzing trends in preventive journalism [109], Amor et al. linked cultural values to CSR practices [110], and Nieto-Librero et al. developed the `Clustering Disjoint HJ-Biplot` to classify pollution patterns [111]. Additionally, Tejedor-Flores et al. combined it with MuSIASEM to examine energy consumption in Ecuador, showcasing the method's utility in sustainability studies [112].

In 2018, the `HJ-Biplot` was extensively applied across diverse fields, with Amor et al. analyzing sustainability behaviors influenced by mimetic forces and legal systems in CSR practices [113,114], while Cubilla-Montilla et al. explored the role of cultural values in improving corporate transparency on human and labor rights issues [115]. Fernandes et al. used the method to address innovation challenges in Portugal [116], and Gallego-Alvarez et al. evaluated environmental performance in Latin America [117]. The technique also revealed climatic and soil impacts on grape composition in Rioja appellation [118] and improved heterogeneity analysis in diagnostic test meta-analyses [119]. It demonstrated its advantages in studying executive functions in Colombian children [120] and disaggregating agricultural data [121]. In 2019, applications included water quality evaluation [122], emotional and intelligence aspects in digital education [123], and CSR policy analysis [124]. Other studies quantified the health impacts of air pollution in Ecuador [125] and exam-

ined innovation in Portuguese start-ups [126], showcasing the HJ-Biplot's adaptability and effectiveness.

In the last few years, the HJ-Biplot has demonstrated remarkable versatility, being applied across diverse fields. Studies have explored educational strategies [127], analyzed CO_2 emissions and family business succession challenges [128,129], and examined correlations between environmental performance, e-government, and corruption [130]. It has been employed to study arterial hypertension risks, corporate sustainability indicators, and innovative behaviors in Ecuadorian universities [131–133]. Applications include analyzing gastric cancer risks linked to Helicobacter pylori in Ecuador [134], innovative time-series analysis techniques [135], and assessing the Chilean economy's focus on common good development [136]. In recent years, the HJ-Biplot has seen innovative advancements and diverse applications. Alvarez and Griffin introduced the GH-Biplot to address multicollinearity in multivariate regression, while Cubilla-Montilla developed the Sparse HJ-Biplot for large datasets, and Martinez-Regalado integrated the HJ-Biplot with machine learning for CSR analysis [72,137,138]. Studies explored economic autonomy among Latin American women, academic performance in Chile, and strategic management in higher education [139–141]. During the COVID-19 pandemic, researchers applied the HJ-Biplot to assess health risks, vaccine strategies, and related conditions, highlighting its utility in managing public health crises [142]. Other works analyzed pension systems in Latin America, food supply impacts on non-communicable diseases in Ecuador, and neuroendocrine tumor survival rates, showcasing the technique's adaptability in addressing societal and health challenges [143–145].

In recent studies, the HJ-Biplot has demonstrated its versatility in addressing diverse challenges. Pilacuan-Bonete et al. integrated it with the Latent Dirichlet Allocation model to analyze COVID-19-related digital news, while Ramiro Miranda et al. evaluated the dietary intake of polyphenols in postpartum women, linking it to nutritional profiles [146,147]. Applications also included assessing COVID-19 vaccination progress in the Americas and Europe as well as introducing disjoint biplots for sustainability analysis [148,149]. Ruiz-Toledo et al. examined the positioning of Latin American universities in global rankings, correlating variables like funding and scientific output, while Torres García et al. analyzed neuropsychological impacts and depression in gender violence victims using this method [150,151]. In 2023, Cano et al. applied the HJ-Biplot to model radiological content in construction materials, Crespo et al. linked crime rates to socioeconomic factors in Ecuador, and Ferreira et al. combined the technique with machine learning to study driving behavior and emissions, further showcasing its adaptability in multivariate analyses [152–154].

Recent advancements highlight the HJ-Biplot's continued evolution and applications. Gonzalez-Garcia et al. introduced the Cenet HJ-Biplot, combining restricted singular value decomposition and elastic net penalization for the improved representation of high- and low-dimensional matrices [71]. Studies also explored the pandemic's impact on tourism and SDGs globally, analyzing corporate commitment to sustainability post-COVID and trends in agroforestry research [155–158]. In 2024, Almorza et al. applied the HJ-Biplot to maritime inspections, while Duran-Ospina used it in bibliometric studies on keratomycosis [159,160]. Ramos-Veintimilla analyzed genetic families of *Juglans neotropica*, emphasizing its value in forest genetics [161]. Saez-Lopez examined gamification in education, revealing limited teacher adoption, and Silva and Freitas enhanced time-series analysis with the SSA HJ-Biplot [162,163]. Applications extended to environmental analysis, from Ecuador's water quality to the environmental impact of food products, offering critical insights for sustainability [164,165].

The chart provided in Figure 10 represents an analysis of the different areas where the seminal `HJ-Biplot` article has been applied, distributing a total of 121 articles across various disciplines. The largest application is found in the field of **Health**, with 18 articles, representing approximately 14.9% of the total. This is followed by the areas of **Sustainability** with 14 articles (11.6%), **Environmental Sciences** with 15 articles (12.4%), and the seminal article and its extensions with 10 articles (8.3%). Additionally, other areas like **Management** (9 articles, 7.4%), **Education** (8 articles, 6.6%), and **Economics** (7 articles, 5.8%) also show a notable level of application for this technique. Other applications include more specific disciplines such as **Bibliometrics** (6 articles, 5.0%), **Psychology** (6 articles, 5.0%), **Agronomy** (5 articles, 4.1%), and **Oenology** (4 articles, 3.3%). The areas with the fewest publications include Criminology, Politics, Journalism, Data Networks, Neuromedicine, and Silviculture, each with fewer than 4 articles, representing a smaller percentage of the total. This analysis indicates a diversification in the applications of `HJ-Biplot` with a significant trend toward its use in health, sustainability, and environmental topics.

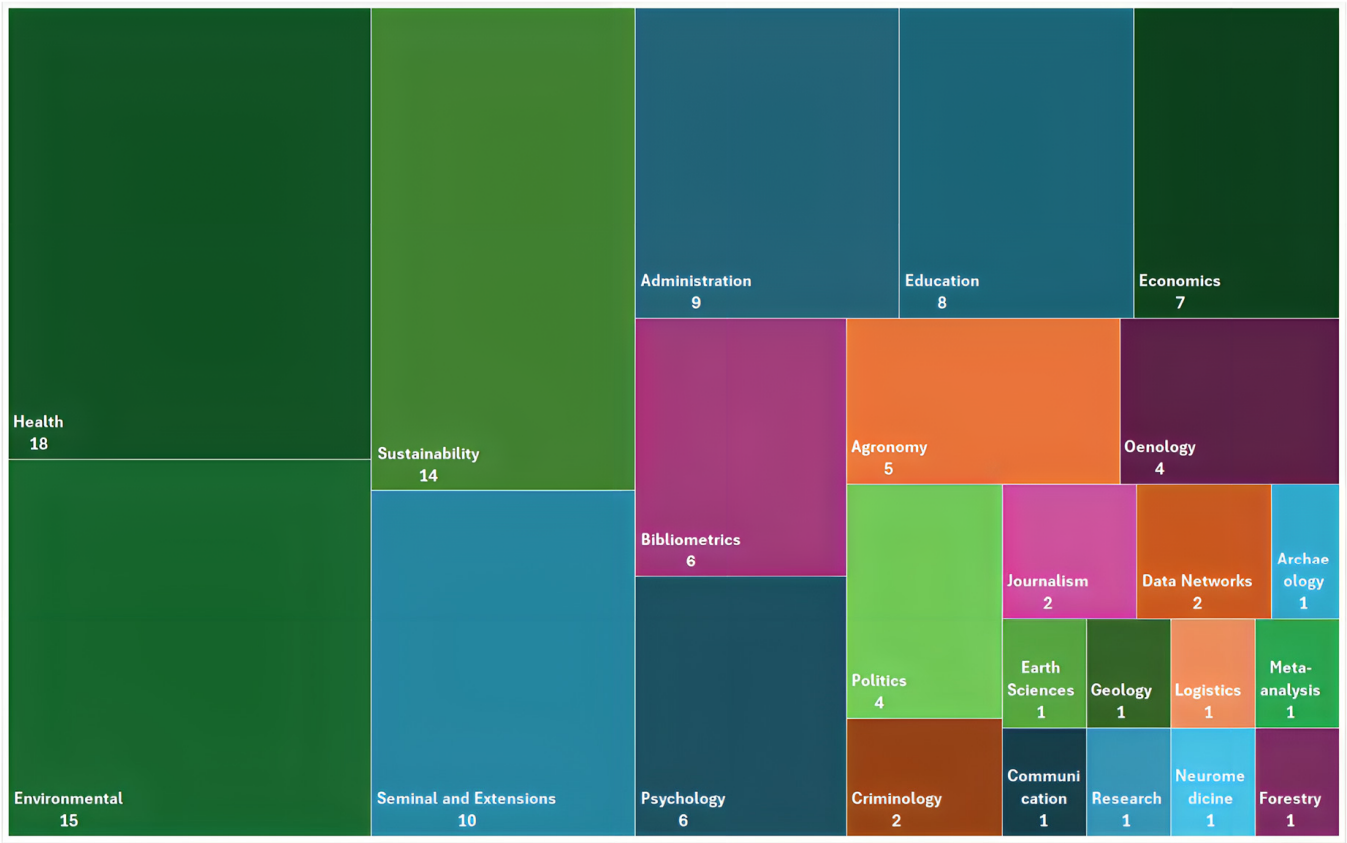


Figure 10. Areas of application of the HJ-Biplot.

Table 7 presents a summary of the different extensions of the HJ-Biplot technique over the years. It starts in 1986 with the original development of the HJ-Biplot in [12]. From 2015 onwards, the emergence of several extensions can be observed, such as the Dynamic Biplot [74] and the Bootstrap HJ-Biplot in [73], which were followed by other significant variants such as the Compositional HJ-Biplot [108], Clustering Disjoint HJ-Biplot [111], SSA HJ-Biplot [135], Sparse HJ-Biplot [72], Cenet HJ-Biplot [71], and finally the ESSA HJ-Biplot in [163].

Table 7. HJ-Biplot techniques and their sources.

Technique	Year	Authors	Journal
HJ-Biplot	1986	Galindo [12]	*Questíio*
Bootstrap HJ-Biplot	2015	Nieto-Librero, et al. [73]	*Colombian Journal of Statistics*
Dynamic Biplot	2015	Egido J; Galindo [74]	*British Journal of Applied Science & Technology*
Compositional HJ-Biplot	2016	Suarez M, et al. [108]	*International Journal of Molecular Sciences*
Clustering Disjoint HJ-Biplot	2017	Nieto-Librero, et al. [111]	*Chemosphere*
SSA HJ-Biplot	2020	da Silva A.O.; Freitas A. [135]	*Statistics, Optimization and Information Computing*
Sparse HJ-Biplot	2021	Cubilla-Montilla, et al. [72]	*Mathematics*
Cenet HJ-Biplot	2023	Gonzalez-Garcia, et al. [71]	*Advances in Data Analysis and Classification*
ESSA HJ-Biplot	2024	da Silva A.O.; Freitas A. [163]	*Advances in Data Analysis and Classification*

Figure 11 shows a detailed timeline of the development of the HJ-Biplot technique, manually created, from its inception in 1986 by Galindo to its most recent extensions and applications in 2024. The top and bottom parts of the graph detail the various applications of the HJ-Biplot and its extensions in different areas of knowledge over time. Since its creation, the HJ-Biplot has found applications in areas such as **Environmental Sciences**, **Health**, **Oenology**, **Bibliometrics**, **Economics**, and **Management**. As the extensions of the technique are developed, an increase in the variety and specificity of application areas is observed. This graph highlights how the use of the HJ-Biplot has evolved to include a multidisciplinary approach, covering both traditional applications and innovative fields in emerging areas. Additionally, it not only highlights the chronological evolution of the HJ-Biplot and its extensions but also the diversification of its applications, demonstrating its continued relevance and expansion in academic and applied research over nearly four decades.

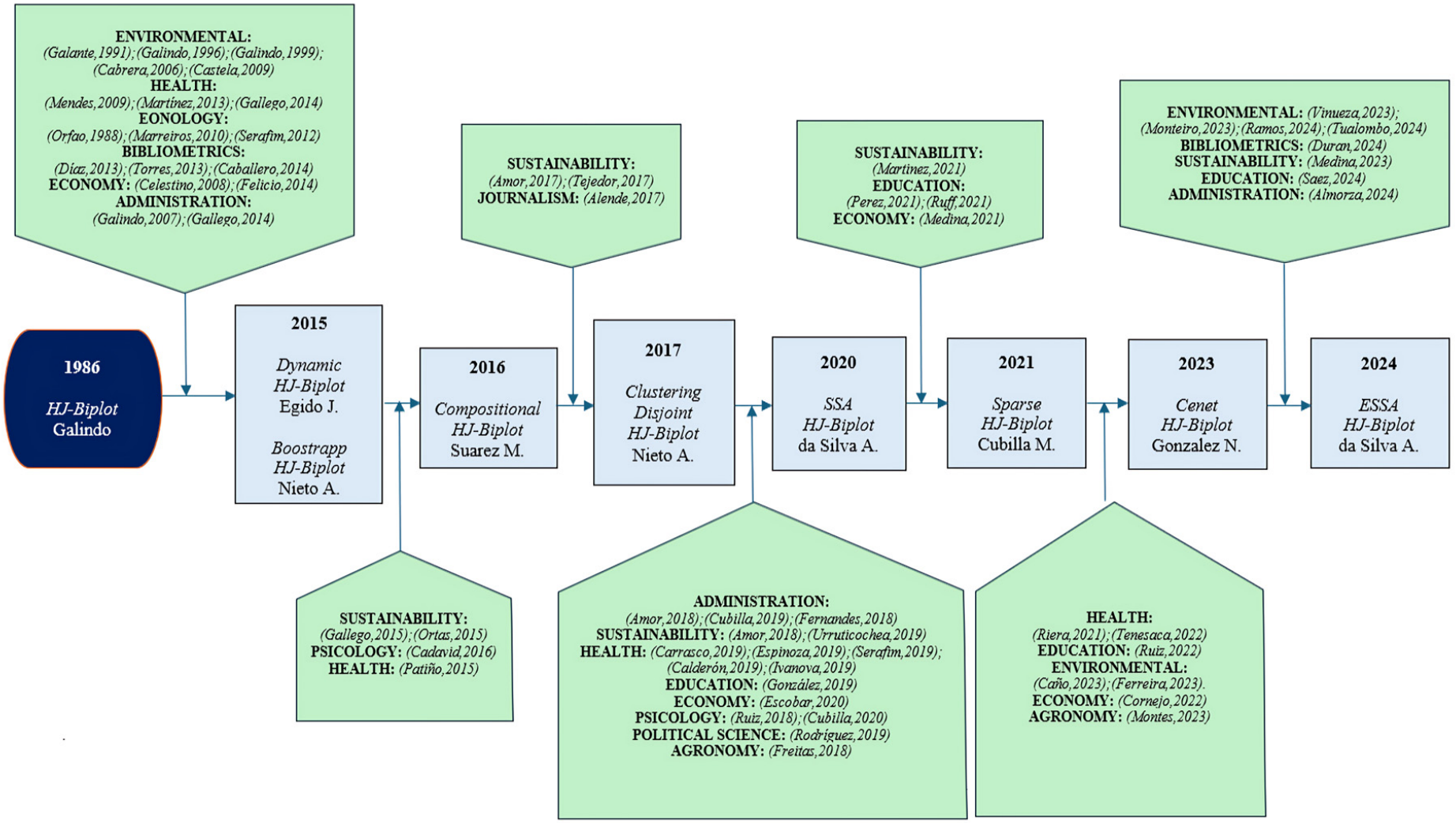


Figure 11. Timeline of the `HJ-Biplot`, extensions, and some applications [12,69,71–76,80,81,85,87–98,104–116,120–125,127,130–132,135,136,138–144,148,150,152,154,156–165].

4. Discussion

The HJ-Biplot has proven to be a powerful and versatile tool in the analysis of multivariate data with notable applications in fields such as health, sustainability, and socioeconomic studies. In the field of health, for example, its ability to identify complex patterns and relationships has enabled significant advances in the identification of risk profiles and the design of personalized interventions. A notable study is [106], which used the HJ-Biplot to analyze lifestyle clusters associated with cardiometabolic risks, providing valuable insights for the prevention of chronic diseases.

In the field of sustainability, the HJ-Biplot has been employed in various applications that analyze environmental, economic, and social indicators. For example, in [104], this technique was applied to evaluate the *Sustainable Society Index*, providing a clear visual representation of countries with the best performance in sustainability. In [110], the HJ-Biplot was used to analyze the relationship between corporate social responsibility and financial performance in European companies, highlighting how sustainable practices can positively influence economic outcomes. Another relevant example is [117], where the HJ-Biplot was applied to assess the impact of environmental policies on greenhouse gas emissions reduction in different regions of the world, identifying the most effective strategies to combat climate change. These studies demonstrate the versatility of the HJ-Biplot in addressing complex problems in the field of sustainability, providing valuable insights for decision making in public policies and corporate strategies.

In socioeconomic studies, the HJ-Biplot has been used to analyze survey data and employment profiles, as in the study [87] on women in irregular employment situations in Salamanca. However, its application in fields such as engineering and technology is less common, despite its potential to address complex problems in these areas. For example, the HJ-Biplot could be used to analyze sensor data in autonomous vehicles or to optimize processes in smart mining, where the identification of patterns and relationships could improve efficiency and decision making. These applications represent opportunities to expand the use of the HJ-Biplot in interdisciplinary and emerging contexts.

An innovative aspect of this work is the combination of text mining techniques and artificial intelligence to analyze large volumes of information. By using tools such as IRAMUTEQ and ChatGPT 3.5, key insights were extracted and synthesized from 121 studies, identifying emerging trends and application areas that might have gone unnoticed with traditional methods. For example, the context provided by ChatGPT 3.5 enabled the generation of a detailed timeline summarizing the evolution of the HJ-Biplot from its introduction in 1986 to the most recent innovations, such as the Sparse HJ-Biplot and the Cenet HJ-Biplot. Additionally, text mining facilitated the identification of thematic patterns in the abstracts of the articles, enriching the analysis and providing a more comprehensive view of the contributions and limitations of the technique. This combination of methods not only enhanced the context of the information obtained but also demonstrated the potential of artificial intelligence to complement and enhance data analysis in systematic reviews.

Despite its wide applicability, the HJ-Biplot faces several challenges that limit its use in certain contexts. One of the main challenges is the integration of heterogeneous data, such as the combination of genomic and clinical data in health studies. Although extensions like the Sparse HJ-Biplot have proven useful for dimensionality reduction in these cases, their interpretation remains complex and requires validation by experts in the field. Another challenge is scalability in large datasets, where techniques such as deep learning could complement the HJ-Biplot to improve the efficiency and accuracy of the analysis. Additionally, the lack of software tools that integrate the HJ-Biplot with

artificial intelligence techniques limits its applicability in emerging fields such as data mining and process optimization.

A key aspect in the future development of the `HJ-Biplot` is the complementarity between its different extensions, such as the `Sparse HJ-Biplot` and the `Cenet HJ-Biplot`. The `Sparse HJ-Biplot` excels in applications requiring dimensionality reduction, such as in genomic data analysis, where its ability to identify key variables is invaluable. On the other hand, the `Cenet HJ-Biplot` offers robustness and flexibility in handling high- and low-dimensionality matrices, being particularly useful in the evaluation of public policies, where it allows for a precise representation of relationships between variables. These complementary characteristics open the door to future developments that integrate both techniques, as well as the exploration of innovative approaches, such as the use of functional data or disjoint techniques, which could further expand the capabilities of the `HJ-Biplot` to address complex problems in various fields. The combination of these extensions and the incorporation of new methodologies promise to enrich multivariate analysis, offering more versatile and adaptable tools to the current needs of research.

To overcome these limitations and fully leverage the potential of the `HJ-Biplot`, several directions for future research are proposed. First, it is crucial to explore the integration of the `HJ-Biplot` with machine learning techniques, such as penalized principal component analysis (Sparse PCA) and neural networks, to improve its scalability and applicability in large datasets. Second, complementary studies between the different extensions of the `HJ-Biplot`, such as the `Sparse HJ-Biplot` and the `Cenet HJ-Biplot`, are recommended to identify their advantages and limitations in different contexts. Finally, the development of software tools that integrate the `HJ-Biplot` with artificial intelligence techniques would facilitate its use in interdisciplinary and big data applications, thereby expanding its reach and relevance in current research.

The `HJ-Biplot` is an invaluable tool for multivariate data analysis with demonstrated applications in multiple disciplines. However, its full potential has yet to be realized, and it is necessary to address challenges such as the integration of heterogeneous data, scalability in large datasets, and the lack of advanced software tools. By overcoming these limitations, the `HJ-Biplot` could establish itself as an indispensable tool in data analysis, offering innovative solutions to complex problems in research and professional practice.

5. Conclusions

Through an exhaustive analysis of the literature employing Galindo's `HJ-Biplot` technique, 121 articles published from 1986 to the present were identified, allowing the mapping of the evolution and diversification of this technique over time. The reviewed studies reveal both significant theoretical contributions and applications in diverse and high-impact areas, such as Health, Environment, Sustainability, Management, and Economics. These fields highlight the versatility of the `HJ-Biplot` in addressing complex and multidimensional issues. Furthermore, it was observed that Spain, Ecuador, Portugal, Colombia, and Chile lead in publication volume, underscoring the relevance of these regions in the development and application of the technique. This geographical focus also suggests possible collaborations and areas for expansion in future studies.

The integration of artificial intelligence through the use of `ChatGPT 3.5` added an extra layer of analysis to text mining, specifically with the `Canonical Biplot`, enriching the context of the data and facilitating the identification of patterns and trends in the reviewed literature. Artificial intelligence proved to be a valuable resource by automating classification processes and semantic analysis, optimizing time, and enabling deeper processing of large volumes of information. However, it is essential to recognize that the use of these tools is not without limitations. The results largely depend on the approach and initial

parameters set by the researcher, which could introduce biases or partial interpretations depending on the methodological decisions made at each stage of the analysis.

Although artificial intelligence has shown great potential in processing and analyzing textual data, it is crucial that the generated data be interpreted with caution. The dependence of AI on learning models trained with prior information may limit its objectivity and, in some cases, introduce automated interpretations that do not necessarily capture the complexity or specific context of the studies analyzed. This underscores the need for researchers to complement AI-generated results with a critical and contextualized review, minimizing potential biases and achieving a more comprehensive and balanced interpretation of the information.

This study, structured into seven methodological phases, provides a robust framework for conducting systematic literature reviews using the `HJ-Biplot` technique. The proposed methodology facilitates the organization and analysis of a high volume of articles, enabling a comprehensive view of the technique's evolution and applications. Despite the density and complexity of the data analyzed, the methodological approach implemented in this work simplifies the identification of key trends and contributions in the field, establishing itself as a valuable tool for researchers interested in multivariate analysis and text mining. Additionally, this methodological structure can serve as a replicable model for other studies aiming to thoroughly analyze the development of techniques or methodologies within specific research areas.

This study not only documents the historical development and applications of the `HJ-Biplot` technique but also provides practical recommendations for researchers, particularly those less familiar with this methodology. To make the most of the `HJ-Biplot`, it is suggested to start with manageable datasets where its ability to visualize multivariate relationships can provide clear and actionable insights. However, it is important to acknowledge its limitations, such as difficulties in handling synonyms, polysemy, or highly dimensional data, which may require the use of extensions like `Sparse HJ-Biplot` or integration with machine learning techniques.

The hybridization of `HJ-Biplot` with artificial intelligence tools, such as automated semantic analysis, represents a significant opportunity to overcome these limitations. For example, the use of natural language processing (NLP) models could improve the interpretation of complex texts, while dimensionality reduction algorithms, such as penalized PCA (Sparse PCA), could optimize the analysis of large datasets. For researchers looking to explore emerging fields, `HJ-Biplot` is recommended as a complementary tool in interdisciplinary studies, where the visualization of multidimensional data can enrich analysis and decision making. Finally, researchers are encouraged to explore interregional collaborations and expand the use of `HJ-Biplot` in less conventional contexts, such as urban sustainability, digital health, or process engineering. By adopting a practical approach and being mindful of its limitations, `HJ-Biplot` can establish itself as an accessible and powerful tool for addressing complex problems in current research.

Author Contributions: Conceptualization, R.C.-Y., P.G.-V., P.V.-G. and J.L.V.-V.; data curation, R.C.-Y., P.G.-V., F.G.-V. and J.L.V.-V.; formal analysis, R.C.-Y., P.G.-V., F.G.-V. and J.L.V.-V.; investigation, R.C.-Y., P.G.-V., F.G.-V. and P.V.-G.; methodology, R.C.-Y., P.G.-V., F.G.-V., P.V.-G. and J.L.V.-V.; writing—original draft, R.C.-Y., P.G.-V. and P.V.-G.; writing—review and editing, R.C.-Y. and P.G.-V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by UNEMI.

Data Availability Statement: Data are available upon request to the correspondence author.

Acknowledgments: The authors thank the reviewers for their comments, which helped improve the presentation of this manuscript.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

References

1. Gabriel, K.R. The biplot-graphic display of matrices with application to principal component analysis. *Biometrika* **1971**, *58*, 453–467.
2. Gabriel, K.R.; Odoroff, C.L. Use of 3D biplots for diagnosing models to fit higher dimensional data. In *Statistical Image Processing and Graphics*; Wegman, E., Depriest, D., Eds.; Dekker: New York, NY, USA, 1986; pp. 73–86.
3. Eckart, C.; Young, G. A principal axis transformation for non-Hermitian matrices. *Am. Math. Soc. Bull.* **1939**, *45*, 118–121. [CrossRef]
4. Householder, A.S.; Young, G. Matrix approximation and latent roots. *Am. Math. Mon.* **1938**, *45*, 165–171. [CrossRef]
5. Rao, C.R. *Advanced Statistical Methods in Biometric Research*; Wiley: New York, NY, USA, 1952.
6. Rao, C.R. *Linear Statistical Inference and Its Applications*; Wiley: New York, NY, USA, 1965.
7. Rao, C.R. The use and interpretation of principal component analysis in applied research. *Sankhya A* **1965**, *26*, 329–358.
8. Good, I.J. Some applications of the singular decomposition of a matrix. *Technometrics* **1969**, *11*, 823–831. [CrossRef]
9. Hill, M. On looking at large correlation matrices. *Biometrika* **1969**, *56*, 249–253.
10. Bennett, J.F. Determination of the number of independent parameters of a score matrix from the examination of rank orders. *Psychometrika* **1956**, *21*, 383–393.
11. Gabriel, K.R.; Odoroff, C.L. Biplot in biomedical research. *Stat. Med.* **1990**, *9*, 469–485.
12. Galindo, M.P. Una Alternativa de Representación: HJ Biplot. *Questiió* **1986**, *10*, 13–23.
13. Benzécri, J.P. *L'analyse des Correspondances: Introduction, Théorie, Applications Diverses, Notamment à L'analyse des Questionnaires, Programmes de Calcul*; Dunod: Malakoff, France, 1973.
14. Galindo, M.P.; Cuadras, C.M. *Una Extensión del Método Biplot y su Relación con Otras Técnicas*; Universidad de Barcelona: Barcelona, Spain, 1986.
15. Galindo, M.P. Contribuciones a la Representación Simultánea de Datos Multidimensionales. Ph.D. Thesis, Universidad de Salamanca, Salamanca, Spain, 1985.
16. Vicente Villardón, J.L. *MULTBIPLOT: A Package for Multivariate Analysis Using Biplots*; Departamento de Estadística, Universidad de Salamanca: Salamanca, Spain, 2008. Available online: https://www.researchgate.net/publication/263442299_MULTBIPLOT_A_package_for_multivariate_analysis_using_biplots (accessed on 5 January 2025).
17. Faria, J.C.; Allaman, I.B.; Demétrio, C.G.B. *BPCA*, Version 1.3-6; Biplot of Multivariate Data Based on Principal Components Analysis [Software]; Embrapa Pecuária Sudeste: São Carlos, Brazil, 2011.
18. Frutos Bernal, E.; Galindo Villardón, M.P.; Leiva, V. *GGEBiplotGUI*, Version 1.0-9; An Interactive Implementation in R for Modeling Genotype by Environment Interaction [Software]; Universidad de Salamanca: Salamanca, Spain, 2013.
19. Nieto, A.B.; Baccala, N.; Vicente-Galindo, P.; Galindo, M.P. Multibiplot Analysis in R. 2015. Available online: https://cran.r-project.org/web/packages/multibiplotGUI/multibiplotGUI.pdf (accessed on 5 January 2025).
20. Egido, J. *dynBiplotGUI*, Version 1.1.6; An R Package Providing a Comprehensive Graphical User Interface for Creating Dynamic, Classical, and HJ-Biplots [Software]; Universidad de Salamanca: Salamanca, Spain, 2014.
21. Reyes, C. *TextMiningGUI*, Version 0.3; Text Mining GUI Interface; 2021. Available online: https://c0reyes.github.io/TextMiningGUI/ (accessed on 5 January 2025).
22. Torres Cubilla, C.A. *PyBiplots*, Version 0.2.1; Python; Python Software Foundation: Wilmington, DE, USA, 2021.
23. Cubilla-Montilla, M.I.; Torres-Cub lla, C.A.; Galindo Villardón, P.; Nieto-Librero, A.B. *SparseBiplots*, Version 4.0.1; An R Package Implementing HJ-Biplot Using Different Penalization Methods and Visualization via ggplot2 [Software]; Universidad de Salamanca: Salamanca, Spain, 2022.
24. Pilacuan-Bonete, L.; Galindo-Villardón, P.; De La Hoz Maestre, J.; Delgado-Álvarez, F.J. *LDABiplots*, Version 0.1.2; An R Package Providing a Web-Based Graphical Interface for Biplot Representations Using Latent Dirichlet Allocation (LDA) Models [Software]; Universidad de Salamanca: Salamanca, Spain, 2022.
25. Silva, A.; Freitas, A. *Areabiplot*, Version 1.0.0; An R Package for Creating Area Biplots Based on Extended NIPALS Decomposition [Software]; Universidade de Coimbra: Coimbra, Portugal, 2022.
26. Nieto Librero, A.B.; Freitas, A. *biplotbootGUI*, Version 1.3; Bootstrap on Classical Biplots and Clustering Disjoint Biplot; The Comprehensive R Archive Network (CRAN): Vienna, Austria, 2023.
27. Vicente-Villardón, J.L.; Vicente-González, L.; Frutos-Bernal, E. *MultBiplotR*, Version 23.11.0; An R Package for Performing Multivariate Analysis Using Biplots [Software]; Universidad de Salamanca: Salamanca, Spain, 2023.
28. Ratinaud, P. *IRAMUTEQ*, Version 0.7 alpha 2; Interface de R pour les Analyses Multidimensionnelles de Textes et de Questionnaires [Software]; Université de Toulouse: Toulouse, France, 2009.
29. *NVivo*, Version 12; [Computer Software]; QSR International: Burlington, MA, USA, 2020.
30. *ATLAS.ti*, Version 9; [Computer Software]; ATLAS.ti Scientific Software Development GmbH: Berlin, Germany, 2021.

31. Reinert, M. Une méthode de classification descendante hiérarchique: Application à l'analyse lexicale par contexte. *Cah. L'Analyse Données* **1983**, *8*, 187–198.
32. Feldman, R.; Sanger, J. *The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data*; Cambridge University Press: Cambridge, UK, 2007.
33. *MAXQDA*, Version 2022; [Computer Software]; VERBI Software: Berlin, Germany, 2022.
34. *WordStat*, Version 10; [Computer Software]; Provalis Research: Montreal, QC, Canada, 2023.
35. R Core Team. *R: A Language and Environment for Statistical Computing*, Version 4.3.1; [Computer Software]; R Foundation for Statistical Computing: Vienna, Austria, 2023. Available online: https://www.R-project.org/ (accessed on 5 January 2025).
36. Ihaka, R.; Gentleman, R. R: A language for data analysis and graphics. *J. Comput. Graph. Stat.* **1996**, *5*, 299–314.
37. *Voyant Tools*, Version 2.0; [Web-Based Software]; Voyant Tools Team: Montreal, QC, Canada, 2023. Available online: https://voyant-tools.org/ (accessed on 5 January 2025).
38. Higuchi, K. *KH Coder*, Version 3; [Computer Software]; Higuchi Koichi (Publisher): Nagoya, Japan, 2022. Available online: https://khcoder.net/ (accessed on 5 January 2025).
39. Souza, M.A.R.; Wall, M.L.; Thuler, A.C.M.C.; Lowen, I.M.V.; Peres, A.M. The use of IRAMUTEQ software for data analysis in qualitative research. *Rev. Esc. Enferm. USP* **2018**, *52*, e03353. [PubMed]
40. Camargo, B.V.; Justo, A.M. IRAMUTEQ: A software for analysis of textual data. *Temas Psicol.* **2013**, *21*, 513–518.
41. Marchand, P.; Ratinaud, P. L'analyse de similitude appliquée aux corpus textuels: Les primaires socialistes pour l'élection présidentielle française. In Proceedings of the 11eme Journées Internationales d'Analyse Statistique des Données Textuelles, Liege, Belgium, 13–15 June 2012; Volume 1, pp. 687–699.
42. *Leximancer*, Version 5.0; [Computer Software]; Leximancer Pty Ltd.: Brisbane, QLD, Australia, 2023. Available online: https://www.leximancer.com/ (accessed on 5 January 2025).
43. *QDA Miner*, Version 6.0; [Computer Software]; Provalis Research: Montreal, QC, Canada, 2023. Available online: https://provalisresearch.com/products/qualitative-data-analysis-software/ (accessed on 5 January 2025).
44. Do Nascimento, D.C.; Lopes, R.E. Textual analysis software: IRAMUTEQ in qualitative research. *Rev. Bras. Pesqui. Saúde* **2018**, *20*, 1–9.
45. Reinert, M. Alceste, une méthode statistique et sémiotique d'analyse de discours. *Rev. Fr. Psychiatr. Psychol. Médicale* **2001**, *5*, 32–36.
46. Rehurek, R. *Gensim*, Version 4.3; [Python Library]; RaRe Technologies: Prague, Czech Republic, 2023. Available online: https://radimrehurek.com/gensim/ (accessed on 5 January 2025).
47. *MonkeyLearn*, Version 3.4; [Web-Based AI Text Analysis Platform]; MonkeyLearn Inc.: San Francisco, CA, USA, 2023. Available online: https://monkeylearn.com/ (accessed on 5 January 2025).
48. Reinert, M. Alceste une méthodologie d'analyse des données textuelles et une application: Aurelia De Gerard De Nerval. *Bull. Méthodol. Sociol.* **1990**, *26*, 24–54. [CrossRef]
49. Glaser, B.G.; Strauss, A.L. *The Discovery of Grounded Theory: Strategies for Qualitative Research*; Aldine Publishing Company: Chicago, IL, USA, 1967.
50. Ratinaud, P.; Dejean, S. IRAMUTEQ: Implantation de la méthode Alceste dans R et extension aux enquêtes ouvertes. In Proceedings of the 8eme Journées Internationales d'Analyse Statistique des Données Textuelles, Lyon, France, 4–6 March 2009; Volume 1, pp. 1–10.
51. Welsh, E. Dealing with data: Using NVivo in the qualitative data analysis process. *Forum Qual. Sozialforschung* **2002**, *3*, 1–15.
52. Sinclair, J.; Rockwell, G. Voyant Tools: See through your text. In *A New Companion to Digital Humanities*, 2nd ed.; Schreibman, S., Siemens, R., Unsworth, J., Eds.; Wiley Blackwell: Hoboken, NJ, USA, 2016; pp. 557–570, ISBN 978-1-118-68058-0.
53. Creswell, J.W.; Creswell, J.D. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 5th ed.; SAGE Publications: Thousand Oaks, CA, USA, 2018; ISBN 978-1-5063-8670-6.
54. Saldaña, J. *The Coding Manual for Qualitative Researchers*, 4th ed.; SAGE Publications: Thousand Oaks, CA, USA, 2021; ISBN 978-1-5297-5999-5.
55. Liu, Y.; Liu, Z.; Chua, T.-S.; Sun, M. Generative AI for text analysis: Opportunities and caveats. *J. Assoc. Inf. Sci. Technol.* **2023**, *74*, 499–513.
56. Vicente Villardón, J.L. Una Alternativa a los Métodos Factoriales Clásicos Basada en una Generalización de los Métodos Biplot. Ph.D. Thesis, Universidad de Salamanca, Salamanca, Spain, 1992.
57. Amaro, R.I.; Vicente-Villardón, J.L.; Galindo, M.P. Manova Biplot para arreglos de tratamientos con dos factores basado en modelos lineales generales multivariantes. *Interciencia* **2004**, *29*, 26–32.
58. Varas, M.J.; Vicente-Tavera, S.; Molina, E.; Vicente-Villardón, J.L. Role of canonical biplot method in the study of building stones: An example from Spanish monumental heritage. *Environmetrics* **2005**, *16*, 405–419. [CrossRef]
59. Vicente Tavera, S. *Biplot Canónico*; Universidad de Salamanca: Salamanca, Spain, 2016.

60. Brown, T.B.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. Language models are few-shot learners. *arXiv* **2020**, arXiv:2005.14165.
61. Radford, A.; Wu, J.; Child, R.; Luan, D.; Amodei, D.; Sutskever, I. Language models are unsupervised multitask learners. *OpenAI Blog* **2019**, *1*. Available online: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf (accessed on 5 January 2025).
62. OpenAI. *GPT-4 Technical Report*; OpenAI: San Francisco, CA, USA, 2023. Available online: https://cdn.openai.com/papers/gpt-4.pdf (accessed on 5 January 2025).
63. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, Ł.; Polosukhin, I. Attention is all you need. In *Advances in Neural Information Processing Systems 30 (NeurIPS 2017)*; Curran Associates, Inc.: Red Hook, NY, USA, 2017; pp. 5998–6008. Available online: https://arxiv.org/abs/1706.03762 (accessed on 5 January 2025).
64. Howard, J.; Ruder, S. Universal language model fine-tuning for text classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Long Papers), Melbourne, Australia, 15–20 July 2018; Volume 1, pp. 328–339.
65. Janiesch, C.; Zschech, P.; Heinrich, K. Machine learning and deep learning. *Electron. Mark.* **2021**, *31*, 685–695. [CrossRef]
66. OpenAI. *ChatGPT: Optimizing Language Models for Dialogue*; OpenAI Blog: San Francisco, CA, USA, 2022. Available online: https://openai.com/blog/chatgpt/ (accessed on 5 January 2025).
67. Li, Y.; Yang, T.; Yao, B. Enhancing text mining with contextual insights: Integrating GPT models in traditional NLP tasks. *J. Comput. Linguist.* **2021**, *47*, 101–120.
68. Yepes-Nuñez, J.J.; Urrutia, G.; Romero-Garcia, M.; Alonso-Fernandez, S. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews Declaración PRISMA 2020: Una guía actualizada para la publicación de revisiones sistemáticas. *Rev. Esp. Cardiol.* **2021**, *74*, 790–799.
69. Julia, D.C.; Galindo, P.V.; Villardón, M.P.G. Grupos de Discusión y HJ-Biplot: Una Nueva Forma de Análisis Textual/Focus Groups and HJ-Biplot: A New Way to The Textual Analysis. *Rev. Iber. Sist. Tecnol. Inf.* **2014**, *E2*, 19–27.
70. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2013; ISBN 3-900051-07-0.
71. González-García, N.; Nieto-Librero, A.B.; Galindo-Villardón, P. C_{enet}Biplot: A new proposal of sparse and orthogonal biplots methods by means of elastic net CSVD. *Adv. Data Anal. Classif.* **2023**, *17*, 5–19. [CrossRef]
72. Cubilla-Montilla, M.; Nieto-Librero, A.B.; Galindo-Villardón, M.P.; Torres-Cubilla, C.A. Sparse HJ biplot: A new methodology via elastic net. *Mathematics* **2021**, *9*, 1298. [CrossRef]
73. Nieto Librero, A.B.; Galindo Villardón, P.; Leiva, V.; Vicente Galindo, M.P. A methodology for biplots based on bootstrapping with R. *Rev. Colomb. Estad.* **2014**, *37*, 367–397. [CrossRef]
74. Egido, J.; Galindo, P. Dynamic Biplot. Evolution of the economic freedom in the European Union. *Br. J. Appl. Sci. Technol.* **2015**, *11*, 1–13. [CrossRef]
75. Orfao, A.; Gonzalez, M.; San Miguel, J.F.; Cañizo, M.C.; Galindo, P.; Caballero, M.D.; Borrasca, A.L. Clinical and immunological findings in large B-cell chronic lymphocytic leukemia. *Clin. Immunol. Immunopathol.* **1988**, *46*, 177–185. [CrossRef] [PubMed]
76. Galante, E.; Garcia-Roman, M.; Barrera, I.; Galindo, P. Comparison of spatial distribution patterns of dung-feeding scarabs (Coleoptera: Scarabaeidae, Geotrupidae) in wooded and open pastureland in the Mediterranean "Dehesa" area of the Iberian Peninsula. *Environ. Entomol.* **1991**, *20*, 90–97. [CrossRef]
77. Santos, C.; Munoz, S.S.; Gutierrez, Y.; Hebrero, E.; Vicente, J.L.; Galindo, P.; Rivas, J.C. Characterization of young red wines by application of HJ biplot analysis to anthocyanin profiles. *J. Agric. Food Chem.* **1991**, *39*, 1086–1090. [CrossRef]
78. Rivas-Gonzalo, J.C.; Gutiérrez, Y.; Polanco, A.M.; Hebrero, E.; Vicente, J.L.; Galindo, P.; Santos-Buelga, C. Biplot analysis applied to enological parameters in the geographical classification of young red wines. *Am. J. Enol. Vitic.* **1993**, *44*, 302–308.
79. Ortega-Meder, M.D.; Rivas Gonzalo, J.C.; Vicente, J.L.; Santos-Buelga, C. Differentiation of grapes according to the skin anthocyanin composition. *Rev. Esp. Cienc. Tecnol. Aliment.* **1994**, *34*, 409–426.
80. Galindo, M.P. Estudio comparativo de ordenación de comunidades ecológicas basado en técnicas factoriales. *Mediterránea. Ser. Estud. Biol.* **1996**, *15*, 55–61. [CrossRef]
81. Galindo, M.P.; Fernández-Gómez, M.J.; Avila-Zarza, C.; Del Río, A.; Fernández-Aláez, M. El análisis HJ-Biplot como herramienta de estudio en un ecosistema acuático. *Stat. Environ.* **1999**, *85*, 123–130.
82. Garcia-Talegon, J.; Vicente, M.A.; Molina-Ballesteros, E.; Vicente-Tavera, S. Determination of the origin and evolution of building stones as a function of their chemical composition using the inertia criterion based on an HJ-biplot. *Chem. Geol.* **1999**, *153*, 37–51. [CrossRef]
83. Alarcón, P.; Rivas, C. Estilos de personalidad y desadaptación social durante la adolescencia. *Psykhe* **2005**, *14*, 3–16. [CrossRef]
84. Iñigo, A.C.; López-Moro, F.J.; Vicente-Tavera, S.; Rives, V. Monitoring of origin and evolution of building stones through their major components. *J. Mater. Civ. Eng.* **2005**, *17*, 440–446. [CrossRef]

85. Cabrera, J.G.; Martínez, M.F.; Mateos, E.M.; Tavera, S.V. Study of the evolution of air pollution in Salamanca (Spain) along a five-year period (1994–1998) using HJ-Biplot simultaneous representation analysis. *Environ. Model. Softw.* **2006**, *21*, 61–68. [CrossRef]
86. Alcántara, M.; Rivas, C. The spatial dimensions of left-right polarization in Latin America. *Política Gob.* **2007**, *14*, 349–390. Available online: https://www.scielo.org.mx/pdf/pyg/v14n2/1665-2037-pyg-14-02-349.pdf (accessed on 5 January 2025).
87. Galindo Villardón, M.P.; Vicente Galindo, P.; Patino Alonso, C.; Vicente Villardón, J.L. Caracterización multivariante de los perfiles de las mujeres en situación laboral irregular: El caso de Salamanca. *Pecunia* **2007**, 49–79. [CrossRef]
88. Celestino Sanchez, M.A.; Gonzalez Garcia, C.S. Socio-economic profile of women micro entrepreneurs in Mexico (micro enterprise as an economic and social unit). *Portes-Rev. Mex. Estud. Sobre Cuenca Pac.* **2008**, *2*, 85–108.
89. Castela, E.; Galindo, P. *Ecological Inference for the Characterization of Electoral Turnout: The Portuguese Case*; No. 2010-1; CIEO-Research Centre for Spatial and Organizational Dynamics, University of Algarve: Faro, Portugal, 2010. Available online: https://ideas.repec.org/p/ris/cieodp/2010_001.html (accessed on 5 January 2025).
90. Mendes, S.; Fernández-Gómez, M.J.; Galindo-Villardón, M.P.; Maranhão, P.; Azeiteiro, U.; Nicolau, P.B. The study of bacterio-plankton dynamics in the Berlengas Archipelago (West coast of Portugal) by applying the HJ-biplot method. *Arquipélago. Life Mar. Sci.* **2009**, *26*, 25–35. Available online: http://hdl.handle.net/10400.2/14024 (accessed on 5 January 2025).
91. Marreiros, A.; Castela, G.; Rebelo, E.; Galindo, P. *The Pathological-Numeric Codification of Public Hospitals in Portugal: Implementation of Mechanisms to Support the Assessment Process of Hospital Clinical Records and Their Relationship with Funding*; No. 2010-2; CIEO-Research Centre for Spatial and Organizational Dynamics, University of Algarve: Faro, Portugal, 2010. Available online: https://ideas.repec.org/p/ris/cieodp/2010_002.html (accessed on 5 January 2025).
92. Serafim, A.; Company, R.; Lopes, B.; Rosa, J.; Cavaco, A.; Castela, G.; Bebianno, M.J. Assessment of essential and nonessential metals and different metal exposure biomarkers in the human placenta in a population from the south of Portugal. *J. Toxicol. Environ. Health Part A* **2012**, *75*, 867–877. [CrossRef]
93. Diaz-Faes, A.A.; Gonzalez-Albo, B.; Galindo, M.P.; Bordons, M. HJ-Biplot as a tool for inspection of bibliometric data matrices. *Rev. Esp. Doc. Cient.* **2013**, *36*, e001. [CrossRef]
94. Martínez-Ferrero, J.; Gallego-Álvarez, I. Application of the HJ Biplot Methodology to Variation Greenhouse Gas Emissions in International Companies. In *International Conference on Modeling and Simulation in Engineering, Economics and Management*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 10–22. [CrossRef]
95. Torres-Salinas, D.; Robinson-García, N.; Jiménez-Contreras, E.; Herrera, F.; López-Cózar, E.D. On the use of biplot analysis for multivariate bibliometric and scientific indicators. *J. Am. Soc. Inf. Sci. Technol.* **2013**, *64*, 1468–1479. [CrossRef]
96. Felicio, J.A.; Galindo, M.P. Governance mechanisms and performance of publicly traded companies. *Int. J. Bus. Manag.* **2014**, *9*, 1–15. [CrossRef]
97. Gallego-Álvarez, I.; Formigoni, H.; Antunes, M.T.P. Corporate social responsibility practices at Brazilian firms. *Rev. Adm. Empres.* **2014**, *54*, 12–27. [CrossRef]
98. Gallego-Álvarez, I.; Vicente-Galindo, M.P.; Galindo-Villardón, M.P.; Rodríguez-Rosa, M. Environmental performance in countries worldwide: Determinant factors and multivariate analysis. *Sustainability* **2014**, *6*, 7807–7832. [CrossRef]
99. Hernández, M.; Espinosa, F.; Galindo, P. Tomato fruit quality as influenced by the interactions between agricultural techniques and harvesting period. *J. Plant Nutr. Soil Sci.* **2014**, *177*, 443–448. [CrossRef]
100. Herrera Ramírez, D.A.; León Peláez, J.D.; Ruiz Rendón, M.; Osorio Vega, N.W.; Correa Londoño, G.; Ricardo, R.E.; Uribe Bravo, Á. Evaluación de requerimientos nutricionales en vivero de especies tropicales empleadas en silvicultura urbana. *Rev. EIA* **2014**, *21*, 41–54.
101. Morillo, F.; Díaz-Faes, A.A.; González-Albo, B.; Moreno, L. Do networking centres perform better? An exploratory analysis in Psychiatry and Gastroenterology/Hepatology in Spain. *Scientometrics* **2014**, *98*, 1401–1416. [CrossRef]
102. Álvarez, F.J.D.; Villardon, P.G. A proposal for spatio-temporal analysis of traffic matrices using HJ-biplot. In Proceedings of the 2015 IEEE International Workshop on Measurements & Networking (M&N), Coimbra, Portugal, 12–13 October 2015; pp. 1–6. [CrossRef]
103. Ferreira, V.; Panagopoulos, T.; Andrade, R.; Guerrero, C.; Loures, L. Spatial variability of soil properties and soil erodibility in the Alqueva reservoir watershed. *Solid Earth* **2015**, *6*, 383–392. [CrossRef]
104. Gallego-Álvarez, I.; Galindo-Villardón, M.P.; Rodríguez-Rosa, M. Analysis of the sustainable society index worldwide: A study from the biplot perspective. *Soc. Indic. Res.* **2015**, *120*, 29–65. [CrossRef]
105. Ortas, E.; Álvarez, I.; Jaussaud, J.; Garayar, A. The impact of institutional and social context on corporate environmental, social and governance performance of companies committed to voluntary corporate social responsibility initiatives. *J. Clean. Prod.* **2015**, *108*, 673–684. [CrossRef]
106. Patino-Alonso, M.C.; Recio-Rodríguez, J.I.; Magdalena-Belio, J.F.; Giné-Garriga, M.; Martínez-Vizcaino, V.; Fernández-Alonso, C.; García-Ortiz, L. Clustering of lifestyle characteristics and their association with cardio-metabolic health: The Lifestyles and Endothelial Dysfunction (EVIDENT) study. *Br. J. Nutr.* **2015**, *114*, 943–951. [CrossRef]

107. Cadavid-Ruiz, N.; Del Río, P.; Egido, J.; Galindo, P. Age related changes in the executive function of Colombian children. *Univ. Psychol.* **2016**, *15*, 1–10. [CrossRef]
108. Hernández Suárez, M.; Molina Pérez, D.; Rodríguez-Rodríguez, E.M.; Díaz Romero, C.; Espinosa Borreguero, F.; Galindo-Villardón, P. The compositional HJ-biplot—A new approach to identifying the links among bioactive compounds of tomatoes. *Int. J. Mol. Sci.* **2016**, *17*, 1828. [CrossRef]
109. Alende Castro, S.; García González, A. Internet and Social Media in the Prevention Journalism Discourse. A Theoretical Proposal and Main Magnitudes. In *Media and Metamedia Management*; Springer: Cham, Switzerland, 2017; pp. 105–111. [CrossRef]
110. Esteban, V.A.; Villardón, M.P.G.; Sanchez, I.M.G. Cultural values on CSR patterns and evolution: A study from the biplot representation. *Ecol. Indic.* **2017**, *81*, 18–29. [CrossRef]
111. Nieto-Librero, A.B.; Sierra, C.; Vicente-Galindo, M.P.; Ruíz-Barzola, O.; Galindo-Villardón, M.P. Clustering Disjoint HJ-Biplot: A new tool for identifying pollution patterns in geochemical studies. *Chemosphere* **2017**, *176*, 389–396. [CrossRef] [PubMed]
112. Tejedor-Flores, N.; Vicente-Galindo, P.; Galindo-Villardón, P. Sustainability multivariate analysis of the energy consumption of Ecuador using MuSIASEM and BIPLOT approach. *Sustainability* **2017**, *9*, 984. [CrossRef]
113. Amor-Esteban, V.; Galindo-Villardón, M.P.; García-Sánchez, I.M. Industry mimetic isomorphism and sustainable development based on the X-STATIS and HJ-biplot methods. *Environ. Sci. Pollut. Res.* **2018**, *25*, 26192–26208. [CrossRef]
114. Amor-Esteban, V.; García-Sánchez, I.M.; Galindo-Villardón, M.P. Analysing the effect of legal system on corporate social responsibility (CSR) at the country level, from a multivariate perspective. *Soc. Indic. Res.* **2018**, *140*, 435–452. [CrossRef]
115. Cubilla-Montilla, M.; Nieto-Librero, A.B.; Galindo-Villardón, M.P.; Vicente Galindo, M.P.; Garcia-Sanchez, I.M. Are cultural values sufficient to improve stakeholder engagement human and labour rights issues? *Corp. Soc. Responsib. Environ. Manag.* **2019**, *26*, 938–955. [CrossRef]
116. Fernandes, S.; Cesário, M.; Castela, G. Modern innovation challenges to firms and cities: The case of Portugal. *J. Technol. Manag. Innov.* **2018**, *13*, 33–42. [CrossRef]
117. Álvarez, I.G.; Rubio, R.G.; Ferrero, J.M. Environmental performance concerns in Latin America: Determinant factors and multivariate analysis. *Rev. Contab.-Span. Account. Rev.* **2018**, *21*, 206–221. [CrossRef]
118. Leibar, U.; Unamunzaga, O.; Fernández Gómez, M.J.; Galindo Villardón, P.; Castro, C.; Aizpurua, A. Benefit of ancillary data acquired at the cooperative level to study soil type and climatic zone influence on berry composition: A case study in Rioja appellation. *Oeno ONE* **2018**, *52*, 119–133. [CrossRef]
119. Pambabay-Calero, J.J.; Bauz-Olvera, S.A.; Nieto-Librero, A.B.; Galindo-Villardón, M.P.; Hernández-González, S. An alternative to the Cochran-(Q) statistic for analysis of heterogeneity in meta-analysis of diagnostic tests based on HJ Biplot. *Investig. Oper.* **2018**, *39*. Available online: https://revistas.uh.cu/invoperacional/article/view/3843 (accessed on 5 January 2025).
120. Ruiz, N.C.; Egido, J.; Galindo-Villardón, P.; Del-Río, P. Advantages of using HJ-biplot analysis in executive functions studies. *Psicol. Teor. Pesqui.* **2018**, *34*, e3426. [CrossRef]
121. Xavier, A.; Freitas, M.D.B.C.; do Socorro Rosário, M.; Fragoso, R. Disaggregating statistical data at the field level: An entropy approach. *Spat. Stat.* **2018**, *23*, 91–108. [CrossRef]
122. Carrasco, G.; Molina, J.L.; Patino-Alonso, M.C.; Castillo, M.D.C.; Vicente-Galindo, M.P.; Galindo-Villardón, M.P. Water quality evaluation through a multivariate statistical HJ-Biplot approach. *J. Hydrol.* **2019**, *577*, 123993. [CrossRef]
123. Calderón Cisneros, J.; Ortiz Chimbo, K.M.; Alcívar Trejo, C.; Espinoza Valdez, K.G.; Vicente Villardón, J.L. Multivariate analysis of emotional aspects and multiple intelligences in the digital era. *Rev. Ibér. Sist. Tecnol. Inf.* **2019**, *2*, 234–244. [CrossRef]
124. Cubilla-Montilla, M.I.; Galindo-Villardón, P.; Nieto-Librero, A.B.; Vicente Galindo, M.P.; García-Sánchez, I.M. What companies do not disclose about their environmental policy and what institutional pressures may do to respect. *Corp. Soc. Responsib. Environ. Manag.* **2020**, *27*, 1181–1197. [CrossRef]
125. Espinoza, J.A.; Torres, E.P.; Castro, D.M.; Romero, B.R.R.; Luna, J.A.S. Aplicación de Encuesta Sobre Enfermedad Pulmonar Obstructiva Crónica (EPOC) y Cuantificación del Impacto en los Diez Puntos de Monitoreo de la Calidad del Aire en la Ciudad San Francisco de Milagro. *Rev. Ibér. Sist. Tecnol. Inf.* **2019**, 245–256. Available online: https://www.proquest.com/openview/a2be2fdf640fbedd8ac3e27682d84a0f/1?pq-origsite=gscholar&cbl=1006393 (accessed on 5 January 2025).
126. Fernandes, S.; Castela, G. Start-ups' accelerators support open innovation in Portugal. *Int. J. Innov. Learn.* **2019**, *26*, 82–93. [CrossRef]
127. González-García, N.; Sánchez-García, A.B.; Nieto-Librero, A.B.; Galindo-Villardón, M.P. Attitude and learning approaches in the study of general didactics. A multivariate analysis. *Rev. Psicodidáct. (Engl. Ed.)* **2019**, *24*, 154–162. [CrossRef]
128. Luis, P.B.; Galindo-Villardón, P. Carbon dioxide emissions: A multivariate analysis HJ-Biplot, clustering biplot and clustering disjoint biplot. In Proceedings of the World Congress on New Technologies, Lisbon, Portugal, 18–20 August 2019. [CrossRef]
129. Chimbo, K.O.; Cabrera, E.C.; Márquez, M.A.; Trejo, C.A. Análisis de las empresas familiares en Ecuador desde una óptica multivariante. *Rev. Cienc. Soc. (VE)* **2019**, *25*. Available online: https://www.redalyc.org/journal/280/28062322012/28062322012.pdf (accessed on 5 January 2025).

130. Rodríguez-Martínez, C.C.; García-Sánchez, I.M.; Vicente-Galindo, P.; Galindo-Villardón, P. Exploring relationships between environmental performance, e-government and corruption: A multivariate perspective. *Sustainability* **2019**, *11*, 6497. [CrossRef]
131. Serafim, A.P.; Martins-Ferreira, A.L.; Serafim, M.P.; Oliveira, G.; Pedro-Rocheta, E.; Pires, N. Prevalência da hipertensão arterial na população portuguesa em contexto de férias e abordagem multivariada dos fatores de risco através do método HJ-Biplot. *Rev. Port. Med. Geral Fam.* **2019**, *35*, 450–464. [CrossRef]
132. Urruticoechea, A.; Vernazza, E. Sostenibilidad empresarial: Análisis a través de la metodología biplot. *Cuad. CIMBAGE* **2019**, *1*, 87–115. Available online: https://dialnet.unirioja.es/servlet/articulo?codigo=10069885 (accessed on 5 January 2025).
133. Jordán, E.D.P.A.; Viteri, R.G.; Guachilema, T.I.R.; Párraga, V.M.V. Comportamiento innovador en la Universidad ecuatoriana: Un análisis multivariante. *Rev. Venez. Gerenc. RVG* **2020**, *25*, 355–367. [CrossRef]
134. Cisneros, J.T.C.; Babici, V.R.; Guerrero, C.A.R.; Villardón, J.L.V. HJ-Biplot multivariate analysis of the occurrence of Helicobacter pylori as a risk for gastric cancer, in the citadel of El Cristo de Consuelo, Milagro Ecuador. *Bol. Malariol. Salud Ambient.* **2020**. Available online: https://www.cabidigitallibrary.org/doi/full/10.5555/20219985150 (accessed on 5 January 2025).
135. da Silva, A.O.; Freitas, A. Time series components separation based on singular spectral analysis visualization: An HJ-biplot method application. *Stat. Optim. Inf. Comput.* **2020**, *8*, 346–358. [CrossRef]
136. Escobar, C.R.; Toledo, M.R.; Pérez, A.M.; Martínez, P.J. Economía chilena: Diagnóstico desde la mirada del desarrollo del bien común. *Econ. Política* **2020**, *7*, 5–49. Available online: https://dialnet.unirioja.es/servlet/articulo?codigo=8765452 (accessed on 5 January 2025).
137. Alvarez, W.; Griffin, V.J. GH Biplot in Reduced-Rank Regression Based on Partial Least Squares. *Stat. Optim. Inf. Comput.* **2021**, *9*, 717–734. [CrossRef]
138. Martínez-Regalado, J.A.; Murillo-Avalos, C.L.; Vicente-Galindo, P.; Jiménez-Hernández, M.; Vicente-Villardón, J.L. Using HJ-Biplot and external logistic biplot as machine learning methods for corporate social responsibility practices for sustainable development. *Mathematics* **2021**, *9*, 2572. [CrossRef]
139. Medina Hernández, E.J.; Fernández Gómez, M.J. La autonomía económica de las mujeres latinoamericanas. *Apunt. CENES* **2021**, *40*, 181–204. [CrossRef]
140. Pérez, A.M.; González, C.P.; Martínez, P.J.; Sánchez, C.V.; Cancino, R.C. Preparatory leveling and academic performance in Bernardo O'Higgins University of Chile. *Rev. Cuba. Educ. Médica Super.* **2021**, *35*, 1–17.
141. Ruff, C.; Ruiz, M.; Flores, T.; Cornejo, C.; Cortés, R.; Matheu, A. Management Model and Strategic Management in Higher Education, Continuous Improvement, and Impact in Rankings. In Proceedings of the World Conference on Information Systems and Technologies, Terceira Island, Portugal, 30 March–2 April 2021; Springer International Publishing: Cham, Switzerland, 2021; pp. 285–294. [CrossRef]
142. Tenesaca, F.; Amaro, I. COVID-19 data analysis using HJ-Biplot method: A study case. *Bionatura* **2022**, *6*, 1778–1784. [CrossRef]
143. Cornejo, C.; Ruff, C.; Benítes, L.; González, J.A.; Galindo, P. HJ-BIPLOT as a Basis for the Search of Clusters Based on Pension Indicators for Latin American Countries. In *Marketing and Smart Technologies, Proceedings of the ICMarkTech 2021, Tenerife, Spain, 2–4 December 2021*; Springer Nature: Singapore, 2022; pp. 107–124. [CrossRef]
144. Ivanova Matamoros, E.; Amaro, I.R.; Fabricio Salinas, J. Statistical Analysis of Mortality by Non-Communicable Diseases (NCDs) and food supply in Ecuador, 1990–2017. *Revis Bionatura* **2019**, *7*, 43. [CrossRef]
145. Escobar, K.M.; Vicente-Villardon, J.L.; Villacís Gonzalez, R.E.; Castillo Cordova, P.H.; Sánchez Rodríguez, J.M.; De la Cruz-Velez, M.; Siteneski, A. Neuroendocrine tumors: An analysis of prevalence, incidence, and survival in a hospital-based study in Ecuador. *Healthcare* **2022**, *10*, 1569. [CrossRef] [PubMed]
146. Pilacuan-Bonete, L.; Galindo-Villardón, P.; Delgado-Álvarez, F. HJ-Biplot as a Tool to Give an Extra Analytical Boost for the Latent Dirichlet Assignment (LDA) Model: With an Application to Digital News Analysis about COVID-19. *Mathematics* **2022**, *10*, 2529. [CrossRef]
147. Miranda, A.R.; Scotta, A.V.; Cortez, M.V.; González-García, N.; Galindo-Villardón, M.P.; Soria, E.A. Association of dietary intake of polyphenols with an adequate nutritional profile in postpartum women from Argentina. *Prev. Nutr. Food Sci.* **2022**, *27*, 20. [CrossRef]
148. Riera-Segura, L.; Tapia-Riera, G.; Amaro, I.R.; Infante, S.; Marin-Calispa, H. HJ-Biplot and clustering to analyze the COVID-19 vaccination process of American and European countries. In Proceedings of the International Conference on Smart Technologies, Systems and Applications, Quito, Ecuador, 1–3 December 2021; Springer International Publishing: Cham, Switzerland, 2021; pp. 383–397. [CrossRef]
149. Cañizares, J.F.R.; Galindo, P.V.; Phillis, Y.; Grigoroudis, E. Graphical sustainability analysis using disjoint biplots. *Oper. Res.* **2022**, *22*, 1575–1596. [CrossRef]
150. Ruiz-Toledo, M.; Ruff-Escobar, C.; Benites, L.; González, J.A.; Galindo-Villardón, M.P. The Place of Latin American Universities in International University Rankings. A Multivariate Statistical Analysis. In *Perspectives and Trends in Education and Technology: Selected Papers from ICITED 2021*; Springer: Singapore, 2022; pp. 163–181. [CrossRef]

151. Torres García, A.V.; Vega-Hernández, M.C.; Antón Rubio, C.; Pérez-Fernández, M. Mental Health in Women Victims of Gender Violence: Descriptive and Multivariate Analysis of Neuropsychological Functions and Depressive Symptomatology. *Int. J. Environ. Res. Public Health* 2021, *19*, 346. [CrossRef]
152. Caño, A.; Suárez-Navarro, J.A.; Puertas, F.; Fernández-Jiménez, A.; Alonso, M.D.M. New Approach to Determine the Activity Concentration Index in Cements, Fly Ashes, and Slags on the Basis of Their Chemical Composition. *Materials* **2023**, *16*, 2677. [CrossRef]
153. Crespo, A.; Brito, J.; Ajala, S.; Amaro, I.R.; Castillo, Z. Multivariate Statistical Techniques to Analyze Crime and Its Relationship with Unemployment and Poverty: A Case Study. In Proceedings of the Computer Science On-line Conference, Online, 3–5 April 2023; Springer International Publishing: Cham, Switzerland, 2023; pp. 180–192. [CrossRef]
154. Ferreira, E.; Macedo, E.; Fernandes, P.; Coelho, M.C. A combined framework of Biplots and Machine Learning for real-world driving volatility and emissions data interpretation. *Sustain. Cities Soc.* **2023**, *99*, 104945. [CrossRef]
155. Matheu, A.; Bustamante, W.; Juica, P.; Ruff, C.; Ruiz, M.; Benites, L.; Cortés, R. Effects of the pandemic on tourism and the Chilean economy, a look from multivariate techniques. *Rev. Tur. Desenvolv.* **2023**, *40*, 113–126. [CrossRef]
156. Medina-Hernández, E.J.; Guzmán-Aguilar, D.S.; Muñiz-Olite, J.L.; Siado-Castañeda, L.R. The current status of the sustainable development goals in the world. *Dev. Stud. Res.* **2023**, *10*, 2163677. [CrossRef]
157. Monteiro, S.; Amor-Esteban, V.; Lemos, K.; Ribeiro, V. Are we doing the same? A worldwide analysis of business commitment to the SDGs. *AIMS Environ. Sci.* **2023**, *10*, 446–466. [CrossRef]
158. Montes-Escobar, K.; De la Hoz-M, J.; Barreiro-Linzán, M.D.; Fonseca-Restrepo, C.; Lapo-Palacios, M.Á.; Verduga-Alcívar, D.A.; Salas-Macias, C.A. Trends in Agroforestry Research from 1993 to 2022: A Topic Model Using Latent Dirichlet Allocation and HJ-Biplot. *Mathematics* **2023**, *11*, 2250. [CrossRef]
159. Almorza, D.; Prieto, J.M.; Amor-Esteban, V.; Piniella, F. Port State Control Inspections under the Paris Memorandum of Understanding and Their Contribution to Maritime Safety: Additional Risk Classifications and Indicators Using Multivariate Techniques. *J. Mar. Sci. Eng.* **2024**, *12*, 533. [CrossRef]
160. Duran-Ospina, J.P.; Maddela, N.R.; Lapo-Talledo, G.J.; Siteneski, A.; Montes-Escobar, K. Global Research on Keratomycosis: New Insights from Latent Dirichlet Allocation and HJ-Biplot-driven Knowledge Mapping Study. *Diagn. Microbiol. Infect. Dis.* **2024**, *110*, 116442. [CrossRef]
161. Ramos-Veintimilla, R.A.; Romero-Cañizares, F.; González-Narváez, M.A.; Castro-Gómez, R.; García-Mora, M.; Fierro-Ricaurte, M.A. Dasometric behavior of genetic families of the threatened forest species Juglans neotropica Diels, collected in the province of Tungurahua, Ecuador. *Afr. J. Biol. Sci.* **2024**, *6*, 1855–1871. Available online: https://www.afjbs.com/uploads/paper/e50a863d60827efdfde91ef9dbe85571.pdf (accessed on 5 January 2025).
162. Sáez-López, J.M.; Grimaldo-Santamaría, R.Ó.; Quicios-García, M.P.; Vázquez-Cano, E. Teaching the Use of Gamification in Elementary School: A Case in Spanish Formal Education. *Technol. Knowl. Learn.* **2024**, *29*, 557–581. [CrossRef]
163. Silva, A.; Freitas, A. An enhanced version of the SSA-HJ-biplot for time series with complex structure. *Adv. Data Anal. Classif.* **2024**, *18*, 409–430. [CrossRef]
164. Tualombo, M.; Amaro, I.; Castillo, Z. HJ-Biplot and Clustering Techniques for Analyzing Water Quality: A Case Study. In *International Conference on Information Technology & Systems*; Springer Nature: Cham, Switzerland, 2024; pp. 17–26. [CrossRef]
165. Vinueza-Cajas, J.; Román-Niemes, S.; Amaro, I.R.; Infante, S. Environmental Impact of Food Products: A Data Analysis Approach Using HJ-Biplot and Clustering. In *International Conference on Advanced Research in Technologies, Information, Innovation and Sustainability*; Springer Nature: Cham, Switzerland, 2023; pp. 324–338. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.