

Hierarchical visualization techniques: a case study in the domain of meta-analysis

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Abstract— *Meta-analysis is a probabilistic technique which groups results from several studies addressing the same topic and produces a result that summarizes the whole. Results generated are graphically displayed without providing interactivity with the user or reproducing a friendly, easy to comprehend interface. In order to obtain a visual exploratory analysis of the most satisfactory results there are Information Visualization techniques which can be applied to map data graphically aiming to broaden the user cognition. This paper presents an analysis of hierarchical information visualization techniques to determine which of them can best represent a data structure, develops meta-analysis and applies information visualization techniques, obtained from the analysis, to the meta-analysis results obtained through the Software R.*

Keywords— *Information Visualization Techniques, Bifocal Tree, Funnel Plot, Dynamic Visualization, Graphic Design, Hierarchy Visualization.*

I. INTRODUCTION

When data is represented in larger and more complex information systems, it is advisable to use some graphic representation. Some authors[1-2]define information visualization (IV) as a science based on the proposal of transmitting some message via graphic elements, improving understanding and facilitating the system maintenance. Visualization techniques (VT) are tools which enable the application of studies developed in IV, with their own characteristics, which allow the presentation of data from differentiated approaches[1].

Neto40 divides VTs into four main groups: geometric, pixel-oriented, iconographic and hierarchical. An evaluation of the techniques in all groups was carried out by Luzzardi[1], employing attributes such as: nature of the domain, data structure, type of information they best represent, type of data, size of domain, operations regarding data and operations regarding data representation. The focus of that study was to compare the techniques usability and not identify the best technique to represent a data structure.

VTs can be used to represent books in libraries, archive directories, browsers and statistical data, among others. One of the areas in which statistical analysis is employed is the meta-analysis.

Meta-analysis is a probabilistic technique which uses the combination of results obtained in several studies and produces results that summarize the data set. This technique can be applied to a fixed or random effects model through the existing software such as the Software R, which is open source free software[10].

The graphs generated by the Software R neither provide interactivity with the user nor reproduce a friendly and easy to comprehend interface. Thus, VTs are important tools to map data resulting from a meta-analysis into a graphic format aiming to broaden the user cognition[11].

Evaluation and classification of information visualization techniques are performed in Shneiderman[38] and Wiss et al[41] requiring user interaction and visual representation attributes on the screen. Luzzardi[1] proposes an evaluation of information visualization techniques based on visual representation attributes and interaction mechanisms.

As there is a large number of existing visualization techniques, a small group was selected for this study: hierarchical visualization techniques (HVT). This paper proposes a qualitative analysis of 18 hierarchical visualization techniques which have been reported in the literature using the criteria presented by Luzzardi[1] and other specific ones which allow the identification of the best hierarchical technique to represent data structure.

The analysis was carried out by employing meta-analysis as a case study in the agronomy field aiming to identify the best technique to represent data to aid decision making regarding whether to use or not the fungicide fluquinconazole in soybean seeds. This fungicide use is important to minimize the effects of a disease called soybean rust.

1.1. Hierarchical Visualization Techniques

Great part of the information belonging to a domain obeys some hierarchical organization. There are: administrative organizations, family trees, disc directories and site addresses, among others. Human beings find it hard to understand certain hierarchy with too many elements, which makes HVTs relevant[3].

HVT are techniques, whose domain data structure and type of information are, respectively, tree and hierarchical information. Johnson and Shneiderman[4] advocate two kinds of information in a hierarchical structure: structural (associated to the hierarchy) and contextual (associated to each element).

Eighteen information visualization techniques were studied to carry out the analysis. Among the HVTs with ideal capability for data structures with under 200 elements are the techniques:

- **CHEOPS[16]:** It is pyramid shaped with triangular nodes. The pyramid height varies according to the tree height. Therefore all the nodes in the last level can be selected, showing their children nodes. Ideal for small hierarchies, such as a simple web page structure.
- **Flip zooming[19]:** enables two-dimensional visualization in which one of the elements occupies half of the screen and the remaining elements occupy the other half. By selecting each element, their respective can be accessed. An ideal technique for small hierarchies (under 200 elements) in which it is important to visualize the content, such as images, text documents, among others.
- **Organization charts[25]:** consists of simple representation trees where the links between elements are straight lines and the nodes can be represented as rectangles or circles. Ideal for data structures with under 100 elements. Widely used with teaching purposes.

When the data structure has from 200 to 500 elements, HVTs can be used, among these are:

- **Bifocal Tree[14]:** It comprises two main areas (context and detail). The first provides a general visualization of the data structure and the second a specific one. The appearance is of a central node with links to the children nodes, which when selected expand to show their respective children. It is an ideal technique for data bases with few children, as the archive directory.
- **Cityscape[17]:** It is similar to a 3D bar chart. The bars occupy the place of plain (city) which grow according to their importance. When selecting one bar, its children are presented in a new visualization.
- **Hyperbolic Tree[21]:** produces visualization so that it is contained in a circle where the main nodes occupy the center and the children nodes are presented in the periphery. Ideal for data structures as archive directory.
- **Icicle Plot[22]:** It is a technique divided into levels according to the tree height grouping nodes and occupying the screen according to the number of elements. It is not recommended when the tree is higher than fifteen.
- **Space Tree[27]:** It was created aiming to improve some of the Hyperbolic tree HVT characteristics, it makes good use of the screen and presents more information of each element. Ideal for small data structure (around five hundred elements).

Among the HVT with CM3 capability (ideal for data structure up to 1000 elements) there are:

- **H-BLOB[20]:** It is bubbled shaped and involves elements belonging to the same parent in the hierarchy. It has multiple levels of detail, enabling to show higher amount of information per element. Ideal for data structures with a lot of information such as books in a library.
- **Perspective Wall[26]:** It is similar to a notice board, where information is presented as rectangles on the wall surface. Ideal for data structures with around 1000 elements.

- **TreeMaps[4]:** It generates a two-dimensional representation on a plain screen where the elements of the same hierarchical level share rectangular regions on the screen and when selected, present a new screen with the level of the node selected. Ideal for both small data structures (archive directories) and larger structures (large libraries).

Among the HVTs with CM4 capability (ideal for data structures with up to 5000 elements) are:

- **Information Cube[23]:** represents information through three-dimensional cubes containing different size texts. It is deal to visualize large data structure (five thousand elements) with little information to be displayed.
- **Sunburst[28]:** It is visually similar to the Information Slices HVT, being different for using only one disc, which when selected presents its children in the same disc. It can be used with data structure of approximately three thousand elements.
- **Time Tube[29]:** It consists of a collection of disc trees positioned in the plain forming a time line. The disc trees are spherical three-dimensional visualizations with sectors. It is deal for hierarchical representations with time changes.

Finally, the HVT group with CM5 capability (ideal for data structures of over 5000 elements) is formed by:

- **Botanical Visualization Tree (BVT)[15]:** It corresponds to a tree-shaped three-dimensional representation where leaves, branches and other elements represent different types of information. It corresponds to the ideal representation of data structures with over ten thousand elements, such as genetic data bases.
- **Cone Tree[18]:** It allows the three-dimensional representation of a tree, with all the operations on data representation. It can be used with smaller data structure (two hundred and fifty elements) or larger data bases (over ten thousand elements).
- **Information Slices[24]:** It enables visualization in the form of a disc with parts, which when selected present a new disc containing the children elements of the node selected. It allows the presentation of large data structures (over five thousand nodes).
- **Table Lens[30]:** It allows the representation of many information dimensions with ideal capability from one hundred to one thousand elements. It is ideal for the visualization of multiple characteristics.

1.2. Meta-Analysis

Unlike the revisions in the literature, which present descriptive work, the meta-analysis uses statistical grouping techniques which combine and analyze results of several studies of a new area aiming to obtain more specific or even definite results[6].

The meta-analysis most important pre-requisite is that the several individual studies approach the same research topic or even examine different aspects of a broader issue[7]. The meta-analysis objectives can be defined as[6]:

- To obtain an ideal central estimate from a series of quantitative estimates.
- To improve the accuracy with which some quantity is estimated.
- To solve an uncertainty when a series of studies present different conclusions.
- To give answers to the issues that are not addressed in any individual study, but that can be examined in subgroups of studies in different systematic contexts.

Although some authors[6-7] only approach quantitative estimates, resulting from several studies statistical calculations, Delahayne et al.[8] explain that both the quantitative and the qualitative approaches are possible in the meta-analysis. Methodological analysis identifies studies which have scientific validity and provides the original research with a qualitative answer[9]. The steps of a qualitative approach carried out through meta-analysis are:

- Formulating the research question.
- Carrying out bibliographical research;
- Defining criteria to judge scientific validity;
- Applying these criteria to each study.

The quality of the statistical accuracy obtained from the meta-analysis depends on the exhaustion of the bibliographic research, that is, it is proportional to the number and quality of the studies found. Some steps to carry out meta-analysis

guarantee the best quality of its results, according to Figure 1[8]. These steps comprise from clearly defining objectives to obtaining effective conclusions.

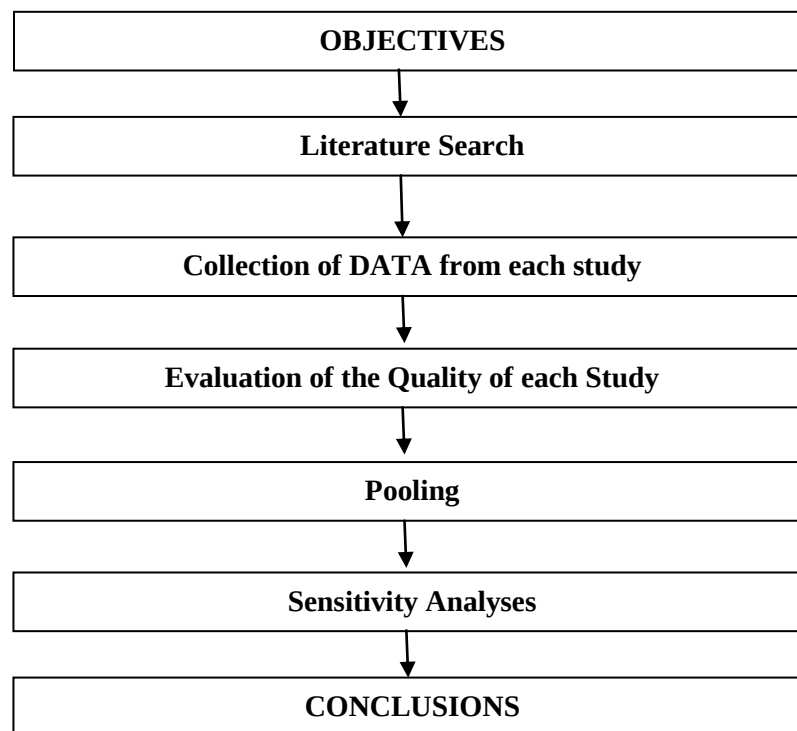


FIG 1. STEPS TO CARRY OUT META-ANALYSIS

In order to combine studies in a meta-analysis it is necessary to determine the measure of effect (ME) and calculate it for each study, thus these studies will be grouped according to the measure adopted. The ME choice depends on the research in question, the kind of variable involved and the number of groups compared. The most used meta-analysis effect measures in experiments are: relative risk (RR), odds ratio and the risk difference[10]. Once the measure of effect has been defined, it is vital to point out the presence, or not, of heterogeneity among the studies classified[10].

1.2.1. Heterogeneity

Different studies might produce different estimates for the same measure of effect. This difference is called heterogeneity and, the larger the distinction is, the higher the heterogeneity is. There are two more usual ways of exploring heterogeneity, which are[10]:

- Cochran Q test: it presents a null hypothesis that the studies included in the meta-analysis are homogeneous. In other words, do not present heterogeneity higher than that randomly expected.
- I^2 of Higgins and Thompson: It is the most direct way of verifying heterogeneity. Its result is presented as a proportion, indicating the heterogeneity percentage value, excluding random effect.

After the heterogeneity between studies has been calculated, it is necessary to choose the most suitable model to the case study, either fixed or random[10].

The fixed model considers that all studies included in the meta-analysis originate from the same population of studies. It is used when the measure of effect is the same in all studies and both present identical characteristics. This model presents a single measure of effect with its respective confidence interval as a result[10].

The random effect model presents a single measure of effect together with the confidence interval as a result. However, this model considers that the measure of effect might not be identical in all studies, presenting variability between them. This model is ideal when the researcher wants to combine several studies which have the same object of study, but that have been conducted in different ways. In such case, the accuracy of results tends to be lower, with a larger confidence interval[10].

The fixed and random effect models are usually employed through statistical software such as the Software R[10].

1.3. R Software

The R Software is defined as a language and environment for computer and graphic statistics. This software has been constantly updated and completed, it is free and open source under the terms of GNU[32].

R provides broad integration of statistical and graphic techniques varieties and is highly extensible, allowing creation and modification of its functions. It is compiled and runs through the Linux, Windows and MacOS platforms[31]. Among several resources, this software has:

- Efficient and easy data manipulation and storage.
- Operation sets for calculation in tables and matrices.
- Simple and efficient programming language, called 'S'.

Regarding statistical procedures, the R Software has several functions such as: linear, generalized linear models, non-linear regression models, time series analysis, classical parameters and non-parametric tests, grouping and leveling[32]. In addition, this software has a library set to carry out meta-analysis.

II. RELATED WORKS

One of the reports in the literature that compares VTs is that of Luzzardi¹, who developed a detailed study in which he compared VTs evaluating them through the usability criteria coming from other authors[35-36-37-38]. As a result, he obtained a set of metrics to evaluate each technique interface. He also defined some elements which can be evaluated in an HVT, which are:

- Domain: context which comprises the elements common characteristics (ex. when representing a library, the domain is the set of books). Thus, regarding the domain, information might be associated to positions in the Euclidean space, take a time variation, be linked to entities and/or linked to relational elements between two or more entities.
- Type of data: It refers to the values used in the representation of each element (ex. an archive directory is represented by symbols which form the directory or file name and icons to represent them).
- Nature of the domain: it can be presented in one of these forms: discrete (quantitative, countable), continuous (qualitative) or continuous-discrete.
- Dimension of the domain: This might be defined in one-dimensional, two-dimensional, three-dimensional or n-dimensional space.
- Search: Consulting some particular information in the visualization.
- Refinement (or filtering): it enables a thorough search (i.e. with more than one attribute).
- Pooling: It consists of cutting elements aiming to simplify visualization.
- Expansion: The capability of inserting more elements even if the technique has already been generated.
- Grouping: The visualizing component can compose groups of elements.
- Selection: The possibility of selecting one or more objects (elements).
- Standpoint: the user can navigate through the visualization.
- Geometric manipulation: rotation, translation, moving operations and scale changes.
- Detailing (zooming): Exhibiting details.
- Undo: The option to undo an action carried out by the user.

III. RESULTS

The results will be presented in three parts. The HVT analysis to determine the best technique to represent data structure, the Meta-analysis application and the Visualization techniques application to the results obtained from the meta-analysis by the Software R.

3.1. HVT Analysis

The selection of eighteen hierarchical techniques to be analyzed in this study followed their appearance in the literature. In order to analyze the HVTs, the attributes presented by Luzzardy[1] were used and two other attributes were added:

- Supported capability: represents the maximum number of nodes in a structure, and is:
- CM1: up to 200
- CM2: up to 500
- CM3: up to 1000
- CM4: up to 5000
- CM5: over 5000
- Algorithm: represents the availability of the algorithm by the author of the technique.

Importantly, in addition to these attributes mentioned above, all the techniques selected for the study are dynamic, ie have interactivity with the user. This attribute was not added to the table because it is common to all techniques.

The attributes listed were divided into two groups, one for the attributes of eliminatory characteristics and another for the classificatory characteristics. Table 1 lists the attributes considered eliminatory, that is, these are HVT necessary attributes to represent the desired data structure.

Each HVT line was filled in using its theoretical principles obtained from the articles about the technique creation as reference. For example, the Bifocal Tree Technique has a domain (DM) linked both to relational elements (REL) and to positions in the euclidean space (PES). The data type (DT) represented by this technique corresponds to both symbolic (SMB) and alphanumeric (AFN), the nature of the domain is discrete (DIS), the domain dimension (DD) is N-Dimensions, which implies that the technique is also three (3D) and two-dimensional (2D) and, finally, the technique has the capability of supporting up to two hundred and fifty nodes (CM2).

One of the contributions of the analysis was filling in Table 1 in which X reports that the technique addresses that attribute and is the base to determine the use of this technique in a data structure desired by the user.

The last line in Table 1, Structure Representation, presents the characteristics that the user desires to represent the data in relation to attributes. For each kind of attribute the user must choose at least one of its subdivisions. For example, when considering the attribute Nature of the Domain (ND), the user must choose one or more options among the subdivisions Discrete (DIS), Continuous (CON) and Continuous-Discrete (CDS), except for the attributes Domain Dimension (DD) and Supported Capability (SC). The choice of all attributes is optional.

In the column Classified Techniques, an X is marked for each technique that satisfies all subdivisions marked in the Structure Representation. This enables to list only the techniques that satisfy mandatory attributes for application. For example, if in the line Structure Representation, the columns Domain linked to relational elements (REL) and the nature of domain is continuous (CON), the techniques which do not have X in the same column can be excluded.

In Table 2, the attributes of classificatory characteristics are listed. It is highlighted that during the use of this analysis this table will only have the techniques previously selected from Table 1.

In Table 2, the line Structure Representation also must be filled in with all attributes that the structure might perform, in addition to the Weight that represents the importance of that attribute for its application. The weight is set using the Likert[34] scale as a reference:

- Weight 5: Extremely important;
- Weight 4: Very important;
- Weight 3: Important;
- Weight 2: Little important;
- Weight 1: Not important at all.

In the column Score, the weights in which the desired characteristic to the user data structure representation is present are added. If there is a draw, the user must decide which technique to use or combine them.

TABLE 1
HIERARQUICAL INFORMATION VISUALIZATION TECHNIQUES AND THEIR ATTRIBUTES OF ELIMINATORY CHARACTERISTIC

TVH	Attributes															Classified Techniques
	DM		DT		ND			DD			SC					
	RE L	PES	SMB	AFN	DIS	CON	CDS	2D	3D	+3D	CM1	CM2	CM3	CM4	CM5	
Bifocal Tree	X	X	X	X	X			X	X	X	X	X				
BVT	X		X			X		X	X	X	X	X	X	X	X	
CHEOPS		X	X	X	X			X			X	X	X	X	X	
Cityscape		X	X	X	X			X	X	X	X	X				
Cone Tree		X	X	X			X	X	X		X	X				
Flip Zooming	X	X	X			X		X	X	X	X					
H-BLOB	X		X			X		X	X		X	X	X			
Hyperbolic Tree		X		X	X			X			X	X				
Icicle Plot		X	X	X	X			X	X	X	X	X				
Information Cube	X		X	X	X			X	X	X	X	X	X	X		
Information Slices	X		X	X	X			X			X	X	X	X	X	
Organization Charts	X	X	X	X	X			X			X					
Perspective Wall	X		X	X			X	X	X	X	X	X	X			
Space Tree	X		X	X	X			X			X	X				
Sunburst		X	X		X			X			X	X	X			
Table Lens		X		X	X			X			X	X	X			
Time Tube		X	X	X	X			X	X		X	X	X	X		
Tree Maps		X	X	X	X			X			X	X	X			
Structure Representation																

DM: Domain (**REL:** Domain linked to relational elements. **PES:** Domain linked to positions in Euclidean space). **DT:** Data type (**SMB:** Symbolic. **AFN:** Alphanumeric). **ND:** Nature of domain (**DIS:** Discrete. **CON:** Continuous. **CDS:** Continuous-discrete). **DD:** Domain dimension (**2D:** Two-dimensional. **3D:** Three-dimensional. **3D+:** N-Dimensional). **SC:** Supported capability (**CM1:** Maximum capacity 200. **CM2:** Maximum capacity 500. **CM3:** Maximum capacity 1000. **CM4:** Maximum capacity 5000. **CM5:** Greater capacity than 5000).

BVT: Botanical Visualization Tree.

TABLE 2
HIERARQUICAL INFORMATION VISUALIZATION TECHNIQUES AND THEIR ATTRIBUTES OF CLASSIFICATORY CHARACTERISTICS

TVH	Attributes of Operations										Algorithm	SCORE
	SRC	REF	POO	EXP	GRO	SEL	STP	GEM	ZOO	UND	YES/NO	
<i>Bifocal Tree</i>		X	X	X	X	X			X			
<i>BVT</i>		X		X	X		X	X	X		X	
<i>CHEOPS</i>			X	X	X	X		X		X		
<i>Cityscape</i>	X			X	X	X	X					
<i>Cone Tree</i>					X	X	X	X	X	X		
<i>Flip Zooming</i>				X		X				X	X	
<i>H-BLOB</i>	X		X	X	X	X		X	X		X	
<i>Hyperbolic Tree</i>	X		X	X	X	X	X			X	X	
<i>Icicle Plot</i>			X	X	X	X	X					
<i>Information Cube</i>	X			X	X		X	X	X	X	X	
<i>Information Slices</i>		X		X	X	X				X		
<i>Organization Charts</i>	X			X		X		X		X	X	
<i>Perspective Wall</i>	X	X		X	X	X	X	X	X	X		
<i>Space Tree</i>			X	X		X			X			
<i>Sunburst</i>	X		X	X	X	X						
<i>Table Lens</i>				X	X	X	X		X			
<i>Time Tube</i>						X	X	X	X	X		
<i>Tree Maps</i>		X		X	X	X		X		X	X	
Structure Representation												
WEIGHT												

SRC: Search. **REF:** Refinement. **POO:** Pooling. **EXP:** Expansion. **GRO:** Grouping. **SEL:** Selection. **STP:** Standpoint. **GEM:** Geometric manipulation. **ZOO:** Zooming. **UND:** Undo. **BVT:** Botanical Visualization Tree.

3.2. Meta-analysis Application

Meta-analysis (MA) is a very popular practice in the medical, pharmaceutical, educational and marketing areas. In agriculture, MA is used to carry out efficacy empirical estimates for the development of productivity and economic investigation[11-12].

The application of meta-analysis to agriculture, proposed in this study, was to identify studies that reported on experiments carried out with the fungicide Fluquinconazole to treat soybean seeds to reduce the effects caused by soybean rust.

A search was carried on the web with the key-words: Fluquinconazole, soybean seed and soybean rust.

Figure 2 illustrates the studies found in the survey. From each study, information was extracted about the experiments and a data base was created called Fluquinconazole Data base, comprising the following attributes:

- Name of the experiment: registering the author's name along with the treatment developed.
- Treatment result: yield obtained with the treatment developed, expressed in Kg/ha.
- Control result: yield obtained in a plot, called control, which did not receive the soybean seed treatment with Fluquinconazole, also expressed in Kg/ha.
- Measure Effect: Difference obtained between the Treatment result and the Control Result.
- Variation coefficient: The statistical coefficient used to evaluate the experiment accuracy.
- Standard error: used to determine each experiment confidence intervals.
- Effect Mean Squares (EMS): a non-biased variance estimator which is used to weigh the averages obtained.

In total, 12 studies were collected with 64 experiments. From these, the increase rate was extracted or not from productivity, appointed as the adopted measure of effect.

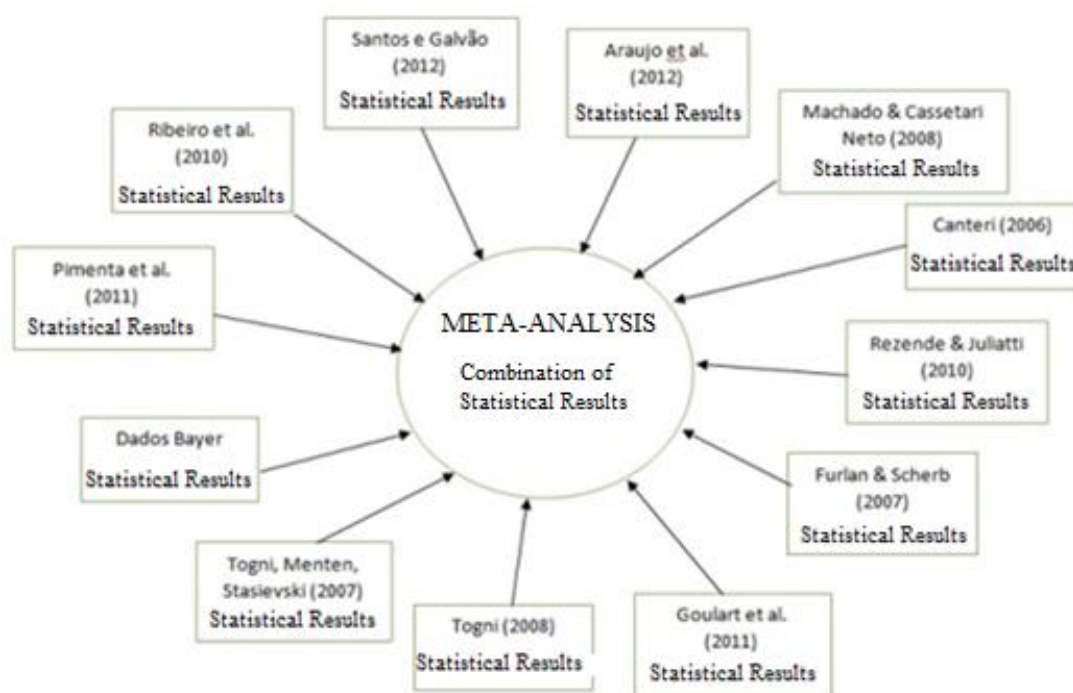


FIG 2. OVERVIEW OF SELECTED SET OF ARTICLES ON THE USE OF FLUQUINCONAZOLE

When the data base was ready, data was compiled by the software R and produced the meta-analysis as a result.

Figure 3 illustrates the graph Funnel plot generated through the meta-analysis calculation carried out with the Fluquinconazole data base. In this figure, the 64 experiments can be seen represented in each point of the image. In the figure, it is not possible to distinguish the studies, since they are equally represented.

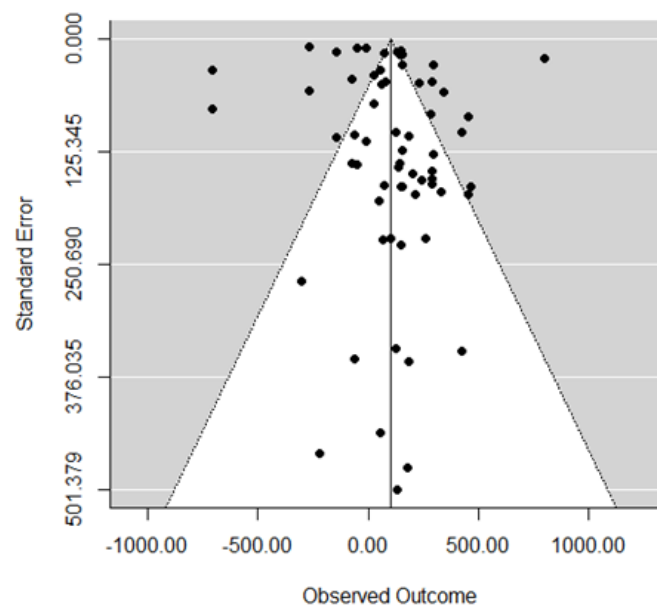


FIG 3. META-ANALYSIS CALCULATION RESULT SHOWN IN THE FUNNEL PLOT GRAPH

The Funnel plot graph is used mainly to illustrate the existence of asymmetries as the presence of publication bias. When it is not detected the presence of publication bias among the studies selected for the meta-analysis, these will form on the graph a similar plot to an inverted funnel. Furthermore, the funnel plot can also be used to detect true heterogeneity (effect size differs according to the study conducted size), data irregularities (poor methodological design of small studies, inadequate analysis) and artifact (heterogeneity due to poor choice of effect measure) [39-40].

The R Software produces answers both in text and graph form (Figure 3). Graphic displays are integral part of the meta-analysis used to facilitate visual communication, highlight important characteristics and exhibit statistical results obtained [33]. In particular, in this study the Funnel plot graph was employed, which is a dispersion graph, used to provide the user with a broad view of the effect that each study provokes to certain meta-analysis.

Each study effect estimates is represented by the x axis, in this case study was used productivity as a measure of effect, versus the effect accuracy measurement, or variance, calculated by R Software to determine the variability of each study, represented by the y axis. Studies with higher number of experiments usually have more accurate effect estimates, with less variability among the studies. These are located more at the top of the graph and smaller studies, with less accurate effect estimates are found more at the bottom.

Langan et al.[33] in their article proposed to add graphic methods which help to illustrate the relevance of adding a new study to the meta-analysis, allowing the researcher to notice whether his/her study is susceptible to alter the significance of the meta-analysis statistics.

However, it is still impossible to identify in the graph which study causes higher impact, or even in which position the study that the researcher wants to identify the significance within the statistical calculations is, since all articles are represented by the same icon, a black circle with the same size. This characteristic might be perfected through the use of hierarchical visualization techniques, in which each study is the parent node and its experiments are the children nodes, and characteristics can be added that can be distinguished in each experiment, for example, a name.

3.3. Applying Visualization Techniques to the Meta-analysis results obtained by the Software R.

The lay-out of Figure 3 can be improved with the use of visualization techniques. In the literature, there are several techniques; in this study 18 were investigated. Which of them could better represent the data in Figure 3? For this identification, the first part of this article results was used.

The data structure necessary to represent in a different way (Figure 3) would: obey some hierarchy, label each element so that it is possible to identify the weight each experiment represents in the meta-analytical result obtained, enable the search for experiments, enable some customized search (eg. Searching variability), expansive visualization, and exhibit each experiment specific characteristics.

Table 3, in the line Structure Representation, presents the characteristics needed to improve data representation. The columns selected were:

- REL: each study can have several experiments; there is a relation between parent node and child node.
- AFN: data structure elements are represented through names not symbols.
- DIS: the nature of the domain is discrete, since the elements must be distributed in the graph from their statistical values.
- 3D: the domain dimension is shown through the effect estimate, effect accuracy and the name of the experiment.
- CM1: the capability needed to represent the 64 experiments, fewer than 200 nodes.

TABLE 3
HIERARQUICAL INFORMATION VISUALIZATION TECHNIQUES AND THEIR ATTRIBUTES OF ELIMINATORY CHARACTERISTIC APPLIED ON FLUQUINCONAZOLE DATABASE

TVH	Attributes															Classified Techniques
	DM		DT		ND			DD			SC					
	REL	PES	SMB	AFN	DIS	CON	CDS	2D	3D	+3D	CM1	CM2	CM3	CM4	CM5	
Bifocal Tree	X	X	X	X	X			X	X	X	X	X				X
BVT	X		X			X		X	X	X	X	X	X	X	X	
CHEOPS		X	X	X	X			X			X	X	X	X	X	
Cityscape		X	X	X	X			X	X	X	X	X				
Cone Tree		X	X	X			X	X	X		X	X				
Flip Zooming	X	X	X			X		X	X	X	X					
H-BLOB	X		X			X		X	X		X	X	X			
Hyperbolic Tree		X		X	X			X			X	X				
Icicle Plot		X	X	X	X			X	X	X	X	X				
Information Cube	X		X	X	X			X	X	X	X	X	X	X		X
Information Slices	X		X	X	X			X			X	X	X	X	X	
Organization Charts	X	X	X	X	X			X			X					
Perspective Wall	X		X	X			X	X	X	X	X	X	X			
Space Tree	X		X	X	X			X			X	X				
Sunburst		X	X		X			X			X	X	X			
Table Lens		X		X	X			X			X	X	X			
Time Tube		X	X	X	X			X	X		X	X	X	X		
Tree Maps		X	X	X	X			X			X	X	X			
Structure Representation		X			X	X				X		X				

DM: Domain (**REL:** Domain linked to relational elements. **PES:** Domain linked to positions in Euclidean space). **DT:** Data type (**SMB:** Symbolic. **AFN:** Alphanumeric). **ND:** Nature of domain (**DIS:** Discrete. **CON:** Continuous. **CDS:** Continuous-discrete). **DD:** Domain dimension (**2D:** Two-dimensional. **3D:** Three-dimensional. **3D+:** N-Dimensional). **SC:** Supported capability (**CM1:** Maximum capacity 200. **CM2:** Maximum capacity 500. **CM3:** Maximum capacity 1000. **CM4:** Maximum capacity 5000. **CM5:** Greater capacity than 5000).

BVT: Botanical Visualization Tree.

In the column Classified Techniques, the only techniques marked with an X are those classified with all the necessary attributes to improve data representation. As it is shown, the techniques classified were Bifocal Tree and Information Cube.

After the table with eliminatory information visualization techniques is applied, those that do not meet the requirements of the data structure are excluded and the table with classificatory information visualization techniques is applied.

Table 4 only presents the techniques with classificatory characteristics. In order to use Table 4, the line Structure Representation has to be filled in with all operational attributes which are needed for the structure, in the line Weight, the importance of each operation attribute must be given and, finally, the result of the column Score of each technique is calculated. As a result, the best adapted technique to represent the data in Figure 3 was the Bifocal Tree, which obtained Score 15, higher than the remaining ones.

After elect the bifocal tree as the best information visualization technique to improve the visual exploration of the data represented in the Funnel Plot graphic, it was possible to apply the technique chosen in the same data structure to perform their validation, through Gephi Software 0.8.242. Figure 4 illustrates the Bifocal Tree technique applied in fluquinconazole database as a graphical alternative to better explore the results generated by the meta-analysis, through their dynamicity.

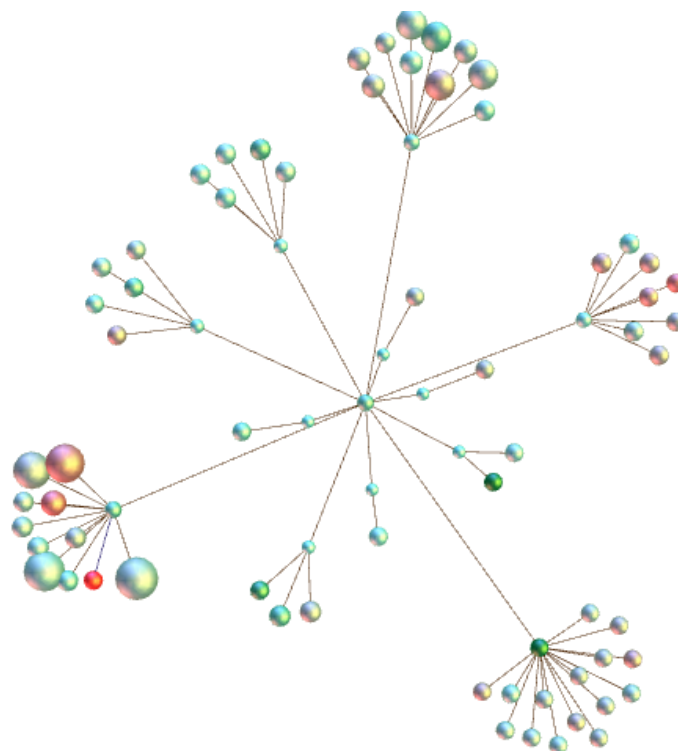


FIG 4. – BIFOCAL TREE TECHNIQUE APPLIED ON FLUQUINCONAZOLE DATABASE

This technique benefits the visual exploitation of resources for a better and faster perception of relevant results. In this case study we used colors and sizes to differentiate the data. The size of the circles is the variability studies. As more variable is the study, the greater its size. The yield, used as a measure of effect, is represented by colors. When negative, yields tend to red, the opposite tends to the green.

Using this feature can be seen if the survey was biased or not through the data variability. Data forming uniform graphics, both in size and in the colors can be judged as biased because if there is no some variability in results, the literature certainly did not include all studies. Also if you wish to identify any study that is represented by the circle, just mousing over the required study and the plot will show its name, as shown in Figure 5.

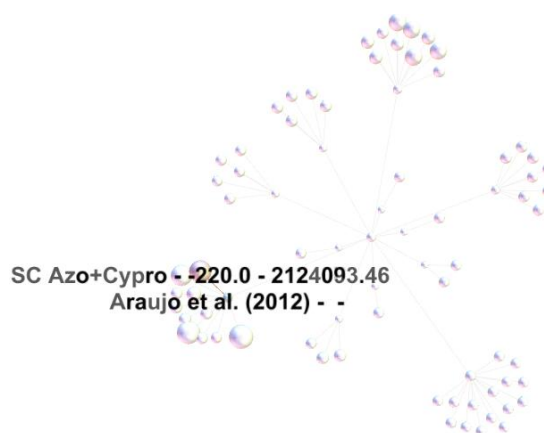


FIG 5. BIFOCAL TREE TECHNIQUE SHOWING THE REQUIRED NAME OF STUDY

The chart dynamically displays the required study and puts in the background the rest. In addition, it presents the study name (Araújo et al 2012), the experiment (SC Azo + Cypro), their respective yield (-220) and variance (2124093.46).

The user also has the data analysis option. Figure 6 is a survey conducted by the user who wants to know what effect measures had a positive result. Of course the graphic displays circles that have only green colors.

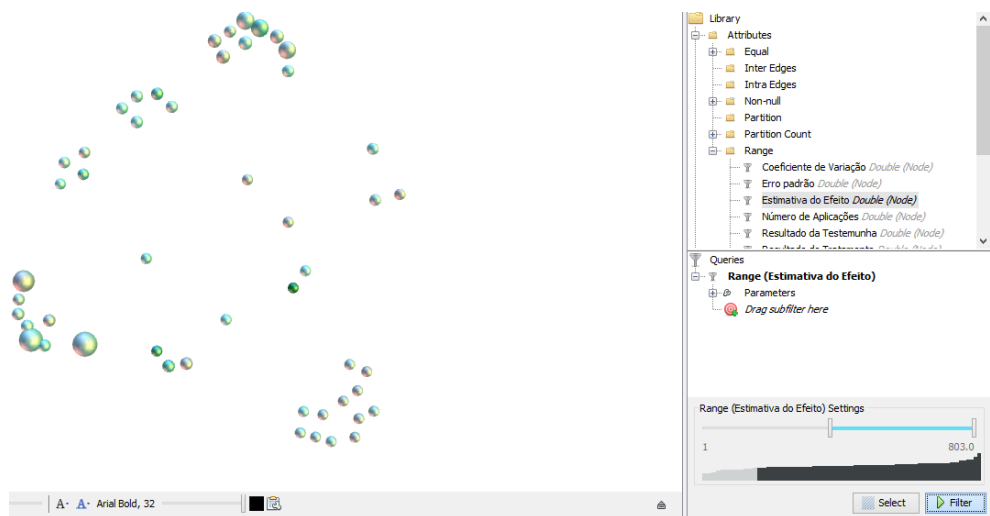


FIG. 6 SEARCH POSITIVE EFFECT MEASUREMENTS

IV. CONCLUSION

This article analyzed 18 hierarchical visualization techniques to create an evaluation process to identify the best technique to be applied to any data structure that can be hierarchically represented.

This process was used to elect the ideal visualization technique which could best represent the Funnel Plot graph, generated by the Software R.

Data plotted in the Funnel Plot graph was the result of meta-analysis carried out to identify the efficacy of the use of the fungicide Fluquinconazole to inhibit soybean rust disease.

The implementation of Bifocal Tree technique to represent the graph data Funnel Plot, developed by Software Gephi showed that the chosen technique could better represent the data structure of fluquinconazole database.

The exploitation of dynamic features offered by the technique resulted in a greater visual exploration, better and faster comprehension of the relevant data, and finally, the analysis of data provided further exploration of the data, and consequently increased the user cognition.

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