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HyperCube4x: Exploring and Analyzing Data in Virtual Reality Using HyperRelational and HyperAnalyzer

Alessandro Rego de Lima[1, 3, *], **Diana Carneiro Machado de Carvalho**[1, 2, †], **Tânia de Jesus Vilela da Rocha**[1, 2, †]

[1]Departamento de Ciências e Tecnologia, Universidade Trás-os-Montes e Alto Douro, Vila Real, Portugal
[2]Instituto de Engenharia de Sistemas e Computadores, Tecnologia e Ciência, Porto, Portugal
[3]Departamento de Ciências e Tecnologia, Universidade Aberta, Lisboa, Portugal

Email address:

1701904@estudante.uab.pt (Alessandro Rego de Lima)
[*]Corresponding author
† Diana Carvalho and Tânia Rocha are co-first authors.

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Abstract: Hypercube is a novel viewport management and information visualization system proposal that introduces three applications (called WorkScenes), focusing on interaction, immersive reading, data exploration, analysis, and visualization concepts. After presenting the conceptual description, interaction metaphors, and the prototype in a previous publication, this article presents HyperRelational and HyperAnalyzer, the WorkScenes focused on multidimensional data exploration, analysis, and visualization. First, the manuscript explores previous work on Human-Computer Interaction-related disciplines, such as cognitive psychology, cognitive engineering, and neuroscience. Then, we introduce HyperRelational and HyperAnalyzer, focusing on their fundamental concepts 1) Geometrical visualization; 2) mapping relationships among information as spatial dimensions. Also, the Screenshots help illustrate the mentioned concepts. Finally, the "Results and Discussion" section demonstrates how these features integrate with the flow, presence, and immersion of Virtual Reality, fit Shneiderman's visual-information-seeking mantra and solve some desktop metaphor-related issues. Additionally, we present test results conducted with 26 participants that show an acceptability rate of 74% amongst users and highlight their positive feedback/experience regarding HyperAnalyzer. On the other hand, the System Usability Scale (SUS) evaluation scored 60.6731. The score demonstrates that HyperAnalyser scored a little better than Microsoft Excel. Therefore, we conclude that the concepts presented here are viable, but it is still necessary to evolve usability to make HyperCube commercially viable.

Keywords: Human-Centered Computing, Information Visualization, Interactive Data, Storytelling, Cognitive Style

1. Introduction

In the first article, we demonstrated that, by taking advantage of the users' natural capabilities, a novel information visualization and management system proposal based on the 4D hypercube could go beyond the traditional desktop metaphor limitations [24]. By exploring new ways of interacting and visualizing information, we introduced 1) a new conceptual description, 2) new interaction metaphors, and 3) a downloadable prototype created to implement the concepts. Also, we released preliminary test results that indicate the users' good acceptance of the concepts and highlight how this new interaction metaphor can improve the user experience.

Following the first proposal based on the 4D -Hypercube, our intention with this article is to demonstrate novel information visualization and data analysis proposals by exploring techniques and concepts, such as interactive data, multidimensional datasets, and OLAP cubes (data-cubes) related to *HyperRelational* and *HyperAnalyzer* workscenes[1]

1 HyperCube4x relates to HyperBook, HyperRelational, and HyperAnalyzer WorkScenes the same way as web browsers to websites.

[22]. The proposal also relies on applying Shneiderman's Visual Information-Seeking Mantra: "Overview first, zoom-and-filter, then details-on-demand" to Virtual Reality systems based on the HyperCube proposal [39].

Finally, we describe the features of *HyperRelational* and *HyperAnalyzer*, two of the three applications created to implement and test new paradigms of visualization, whose potential and benefits are compared with traditional applications, as described below:

1) Describe the relationships among information as spatial dimensions from a geometric viewpoint;
2) Use the magic cube as a paradigm for identifying patterns in data;
3) Present the data in different layouts and parallel planes;
4) Explore dynamic form capabilities to create master-detail navigation for structured data and information disposition optimization.

This article is organized as follows. First, the "literature review" section explores previous work on disciplines focused on the intersection between human and computer capabilities and limitations, such as cognitive psychology, cognitive engineering, and neuroscience, Human-Centered Computing (HCC), Information Visualization (InfoVis), data analytics, and similar. Then, in the "hypercube data interaction and visualization proposal" section, the concepts are described and illustrated with screenshots. Next, we present and discuss the acceptability and usability tests conducted with 26 participants in the "Results and Discussion" section, comparing the HyperRelational and HyperAnalyzer concepts and techniques with traditional and emerging proposes, highlighting how they fit, complement, or diverge. Finally, in the "Conclusion and Future work" section, there is a roadmap for deepening the validation of the hypercube metaphor and final considerations.

2. Literature Review

Human-computer interaction (HCI), data analysis, and information visualization are intrinsically related to technology, perception, and cognition. However, technology was a critical limitation, and knowledge about the physiology of perception and cognition is recent [20]. Therefore, it is challenging to think of effective interfaces in the past. Nevertheless, as technology evolves, more resources become available to create human-centered interfaces skilled at exploring human-brain capabilities and aiding users to bypass physiological limitations.

This review focuses on disciplines studying the intersection between human and computer capabilities and limitations, aiming for a symbiotic integration, such as cognitive psychology, cognitive engineering, and neuroscience. Technology and cognitive science are evolving quickly nowadays. However, placing technology to match human needs is not simple because it depends on overcoming current HCI paradigms, which are difficult to change.

2.1. Human-Centered Computing (HCC)

One critical problem in current HCI is the gap between human behavior and computing technologies. Unfortunately, even the leading suppliers concentrate on improving existing technologies or solving specific problems, not fulfilling this gap [7]. Human-Centered Computing (HCC) aims at combining human sciences (e.g., social and cognitive) and computer science (e.g., Human-computer interaction (HCI), signal processing, machine learning, and ubiquitous computing) for the design of computing systems with a human focus [37].

Jaimes et al. proposed three core factors that HCC should consider: 1) human abilities and limitations; 2) social and cultural environments; and 3) an adjustable system that fits diverse individuals and specific environments, while Shneiderman enforces that it is essential to consider the user's personal, social, and cultural contexts [17, 40]. Therefore, user-centered design is a multi-stage problem-solving process requiring designers to foresee how users will use an interface regarding their behavior [18].

Human-Centered Data Science (HCDS) is the intersection of HCI, computer-supported cooperative work (CSCW), and statistics that combines the richness of qualitative methods and the power of extensive data sets to uncover social nuances considering ethics and values in data use [2]. From the HCI perspective, big data and other analytics-specific visualization have many issues, e.g., data science tools usually are single-user oriented [28]. Moreover, in a typical data science project, dealing with data or data wrangling consumes 50%-80% of the time before any feasible analysis, even using self-service business intelligence tools and advanced analytic solutions [32, 11]. Thus, drawing insights through these visualizations is still effortful and unaffordable.

2.2. Big Data

Big data is an umbrella concept that refers to the exponential growth and availability of structured and unstructured data. Consequently, new terms and concepts grow around it, such as data lakes[2], fast data[3], and thick data[4] [27, 1]. In all cases, data are transformed into data cubes to be analyzed.

A data cube is a multidimensional representation of data. Each cell results from an aggregation function (SUM, AVG, MAX, MIN) described by analysis axes corresponding to the cube's dimensions. A dimension is a hierarchical organization, so facts are observable in different levels of granularity depending on the user's needs [22]. Besides concepts, new exploration techniques arise, aiming for better performance and ease of use.

Sarawagi et al. use prediction by building a learning base from the initial data cube and another one with predicted values calculated using log-linear regression. The system signs deviations between them that indicate exceptional values for the user to explore [35]. Cheng predicted new facts by generating a cube using a generalized linear model [6]. Finally, Han et al. proposed predicting a new fact measure by

2 massively scalable storage repository that holds a vast amount of raw data, i.e., data that are not ready for analysis.

3 the application of big data analytics to smaller datasets to solve specific issues.

4 an ethnographic approach to uncover meaning from big data.

identifying subsets of remarkable data [12].

In a different approach, the information interaction process described by Tom is a loop that cycles until a satisfactory amount of information is retrieved and integrated. First, users choose a specific goal or examine data as a whole. Next, they select or query a subset of information and scan it. Finally, if they detect a cue, they analyze the data, searching for something relevant [46].

2.3. Information Visualization (InfoVis)

Conceptually, Information Visualization (InfoVis) is the exhibition of data in an external representation so that human visual mechanisms process it better [52]. External representations are words, pictures, graphs, tables, and equations that physically embody a problem and refer to the "external code" introduced by Yackel (1984) [49, 44].

The reasons for external representations that make visualization attractive are numerous, as follows: 1) reduce short-term and long-term memory load; 2) optimize perception while lowering the need to interpret and express the information explicitly; 3) Provide knowledge unavailable from internal representations; 4) support perception to identify patterns and make inferences objectively; 5) orient cognitive behavior without conscious awareness; 6) generate more efficient action sequences; 7) make invisible and transient information visible and notorious; 8) Aid objectivity by reducing abstraction; 9) simplify decision-making strategies increasing precision and reducing effort [52].

Information visualization is an interdisciplinary science concerned with enhancing the understanding of complex data using visual representation [51]. Thus, it draws from such disciplines as computer science, graphic design, psychology, mathematics, and business, aiming to leverage visual performance to provide insight that helps users solve problems, to think, reason and comprehend data [29, 14, 5, 15].

High-level cognition, such as insights, reasoning, and understanding, is accomplished by visualization techniques because visual perception has unique properties, is attuned to graphical images, and performs pattern recognition [5, 14, 15]. Therefore, vision is the gate through which computer graphics-generated information reaches the brain, i.e., the door for perception and communication; cognition refers to the processing induced by such graphics. Thus, vision and cognition are intimately connected and crucial in visualization design [34].

Vision Science proposes that the visual process occurs in two stages: preattentive processing and a slower detailed scan. The former performs a parallel low-level property extraction, improving data comprehension [48]. The latter addresses conventional reading practices that do not contribute toward faster cognition but are necessary for further analysis. As highlighted by Rodrigues-Jr et al., the scientific explanation matches the empirical experiment, which resulted in Shneiderman's "visualization mantra": overview first, zoom and filter, then details on demand [34, 39].

Patterson et al. presented a visualization framework that defines a set of six aspects of human cognition valuable for visualization designers: "1) exogenous attention; 2) endogenous attention 3) chunking; 4) reasoning with mental models; 5) analogical reasoning; and 6) implicit learning" [29]. Therefore, the framework stimulates the underlying cognitive processes that induce insight, reasoning, and understanding [29]. For example, exogenous attention is stimulus-driven instead of endogenous attention, which is goal-directed [10]; Chunking refers to the mental process of grouping elements into larger units based on their meaning [26].

The idea is to promote the efficient use of the human visual system to process information that would otherwise require more cognitive effort and relies on processing data in parallel, even bypassing the limited human working memory [52]. Therefore, visual depictions of information enable the users to understand the patterns and trends contained within the plethora of ever-growing datasets [33].

2.4. Storytelling and Information Visualization

Research on narrative visualization considers how storytelling enhances visualization as a communication medium [36]. Storytelling will likely trigger interaction and data exploration once it contextualizes and highlights initial questions. Storytellers (e.g., online journalists) increasingly integrate visualizations into their narratives, sometimes using them to replace a written story [38]. Therefore, storytelling in data visualization is rising by combining complex visualizations and narratives to explain growing numbers [47].

After reviewing 51 online visualizations to understand how narrative devices affect reader interpretation, Hullman & Diakopoulos posit that decisions occur in four layers: data, visual representation, textual annotations, and interaction [16]. In other research, Segel & Heer identified distinct genres and effective narrative devices, such as tacit tutorials, semantic consistency, and matching on content, by analyzing 58 narrative visualizations [38].

Wang et al. conducted an iterative design process resulting in six templates for presentation and visualization: anatomy, construction, visual patterns, pitfalls, false friends, and well-known relatives. Then, a qualitative user study using 11 participants demonstrates the readability and usefulness of the artifacts [50].

Storytelling would trigger information interaction by providing preliminary questions encouraging users to explore data [38]. However, an experiment conducted by Boy et al. indicates that augmenting exploratory visualizations with introductory 'stories' does not appear to increase user engagement in data exploration [4].

2.5. Cognitive Style, Cognitive Engineering

Although regarded as the most powerful cognitive tool, traditional information visualization systems do not consider individual user differences, even though human cognitive abilities and styles are significantly different. Therefore, it is necessary to supply this gap by developing adaptive systems to 1) infer individual user styles and 2) customize the system to reflect inferred features [42].

Conati et al. researched devised user-adaptive visualizations, which adjust to each user's specific needs and abilities in real-time based on 1) analyzing the influences of user traits on visualization effectiveness, 2) user modeling, and 3) the use of eye-tracking to build user and task models [8]. The cognitive abilities of perceptual speed, visual working memory, and verbal working memory influence performance and preferences [45]. Besides, there is an interaction between perceptual and cognitive limits and task demands [13]. Thus, the strict limits of attention firmly reduce information visualization effectiveness, especially the ability to detect unexpected evidence [13].

Cognitive abilities relate to physiologic issues, while cognitive style refers to the preferred modes of processing information [43]. For both of them, individual differences significantly influence user behavior with different user interfaces, including InfoVis systems [42]. Cognitive engineering emerged in the 1980s to elaborate computational artifacts that make interaction fluid and navigation easier considering these aspects [30, 31].

2.6. Spatial Cognition

Research has shown that action games stimulate sensory, perceptual, and attentional abilities such as contrast sensitivity, spatial resolution, visual field, and multiple objects tracking core for spatial cognition [41]. It is necessary to emphasize that "spatial" means a generic area or location, while "geographical" is a subclass of spatial that refers to the earth's surface [25]. Thus, both are related when talking about mental models and spatial reasoning.

The mental model theory assumes that people rely on their understanding of the premises and general knowledge before applying any formal inference rule [19]. In contrast, a mental model in spatial reasoning represents the spatial arrangements between objects that correspond to the premises [9].

Ballatore argues that a spatial element is at the foundation of information search and makes an analogy to biological organisms exploring the physical environment for food. However, although pervasive in many disciplines, including computer science, geographic information science (GIScience), and cognitive psychology, the spatial dimension of the information search is limited in interaction and exchange of experiences [3].

Mark (1983) classifies the "sources of spatial information for cognition" as 1) haptic spaces, which are primordial and defined by touching and bodily interaction; 2) pictorial spaces referring to visual experiences; and 3) transperceptual spaces about inference during wayfinding [25].

The literature review did not uncover any proposal for 1) describing relationships among information as spatial dimensions; 2) using the magic cube as a paradigm for identifying patterns in data visualization.

3. The Hypercube Data Interaction and Visualization Proposal

The hypercube metaphor's data interaction and visualization proposal draw from the following principle: exploring spatial relationships to reduce cognitive load and enhance learning and productivity. Three applications, called workscenes, implement the peculiarities of each type of data interaction, as follows: 1) HyperBook deals with unidimensional data, i.e., discursive text, images, and any sequentially interpreted data; 2) HyperRelational – for 2D and 3D data such as spreadsheets and relational data; 3) HyperAnalyzer – multidimensional data.

The literature treats multidimensional datasets as n-dimensional cubes, as shown in the previous section. As such, representing those dimensions as geometric shapes allow testing whether the geometric shapes' properties aid in visualization and data analysis. Figure 1 illustrates how it works:

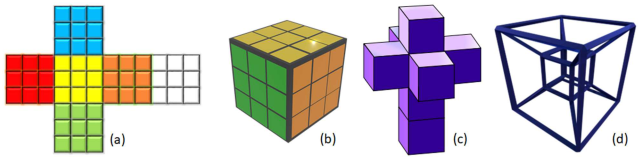

Figure 1. *(a) unfolded cube, (b) cube, (c) unfolded tesseract, (d) tesseract.*

Figure 1 (a) shows an unfolded cube, i.e., a three-dimensional object unwrapped on a bi-dimensional surface. Notice that all sides of the cube are visible, but spatial relations are lost. Next, in (b), the cube's shadow is projected on the bi-dimensional surface. In contrast, the projection keeps spatial relations, but the hidden sides are not visible. Finally, (c) and (d) show that the unfolding and projection affect the tesseract, the 4D-hypercube, similarly. However, as the number of dimensions of the tesseract is higher than that in the real world, the visual effect is slightly different.

Geometrical visualization draws from this dilemma: depending on the situation, the unfolded view is more suitable, even losing spatial relationships. However, in other cases, spatial relationships are part of the analysis. Once there is no single way to handle it, HyperRelational and HyperAnalyzer offer data interactions and visualization options for fast switching from one view to another or maintaining views in parallel planes.

3.1. HyperRelational: A Relational Data Analyzer

A spreadsheet manages data in rows and columns. Therefore, it is a plain object because data in cells depend on a "row header" (i.e., a primary key) and column header to be meaningful. The connection between two tables (e.g., through a join command) mimics figure 1 (a) once data from both tables are available on the same plane. In contrast, the master/detail disposition imitates figure 1 (b) since it keeps information on each table in different places. Therefore, the entity-relationship model organized data in a 3D cube. In contrast, it is also necessary to deal with metadata to discover new ways to join information scattered throughout the collection.

HyperRelational treats structured data in diverse formats, such as proprietary RDMS[5], csv, xml, and json. The aim is to provide data and metadata exploration options drawn from

5 Relational Data Management System

geometrical visualization properties, as shown in figure 2:

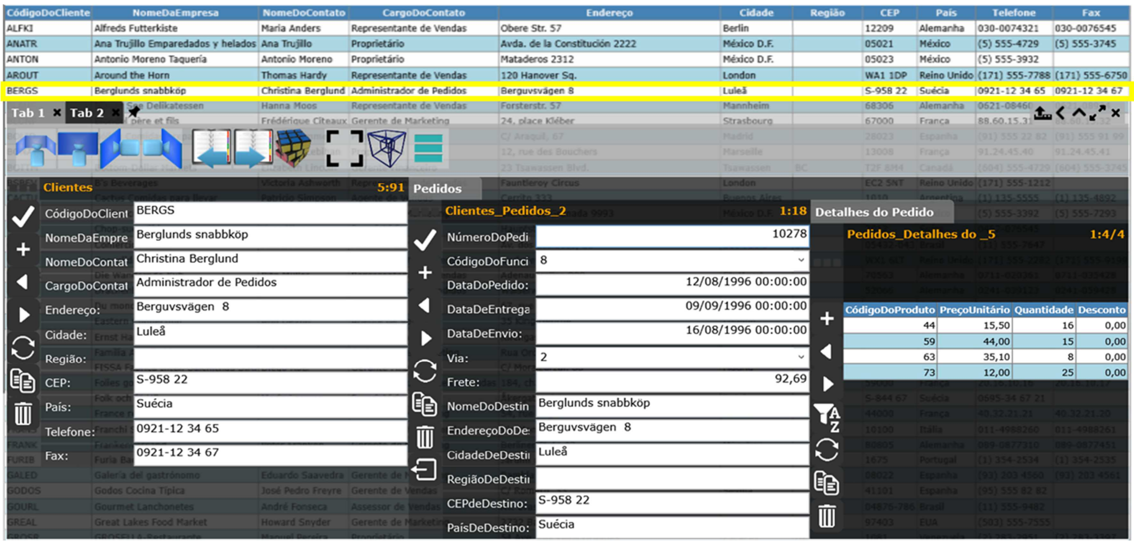

Figure 2. *A table in the grid and master/detail view.*

In figure 2, the grid view in the background is a "plane overview" of the table, while, in the foreground, "tab1" exhibits a master/detail form. If the user clicks a row in the first detail, another form appears until the innermost table is reached. In another tab, i.e., tab2, the user would keep the metadata of the main table. HyperRelational creates the forms dynamically. The master form is a one-column style for better readability, but users can change the number of columns. If the table has more than one relation, each "detail grid" occupies a different tab.

3.2. HyperAnalyzer: A Data Cube Analyzer Proposal

Suppose a dataset with three columns, two of them "groupable" (i.e., a GROUP BY applicable column) and one "aggregable" (i.e., used in SUM, COUNT, AVG functions in a SELECT part of the SQL clause). This dataset is explored as the 3D cube in figure 1 (b). In contrast, traditional OLAP visualization handles these datasets as unfolded cubes, as shown in figure 1 (a), i.e., prejudiced understanding by spatial relations loss. Adding "groupable" and "aggregable" columns to the dataset turns it into a multidimensional dataset. When users analyze each dataset in sequence, they behave as unfolded tesseract figure 1 (c). In contrast, figure 1 (d) shows the combination of the dataset for simultaneous visualizations maps.

HyperAnalyzer deals with these issues by offering complementary ways to visualize information combined with Shneiderman's mantra to allow users to choose the visualization strategy that best fits their needs. First, the user prepares data in HyperRelational by delimiting the number of columns, transposing, adding customized calculations, generating graphs, and creating new faces with these transformed data. Then, the user would sequence (for storytelling-like presentation), compare side-by-side, use the "depth and surface" technique, and so on.

Figure 3 shows a 3-column dataset in the initial standard view 1) figure 3 (a) contains a summary table and pie chart generated by column label and total column; 2) figure 3 (b), a summary table and bar chart generated by row label and row total; 3) figure 3 (c) the full table split into two faces.

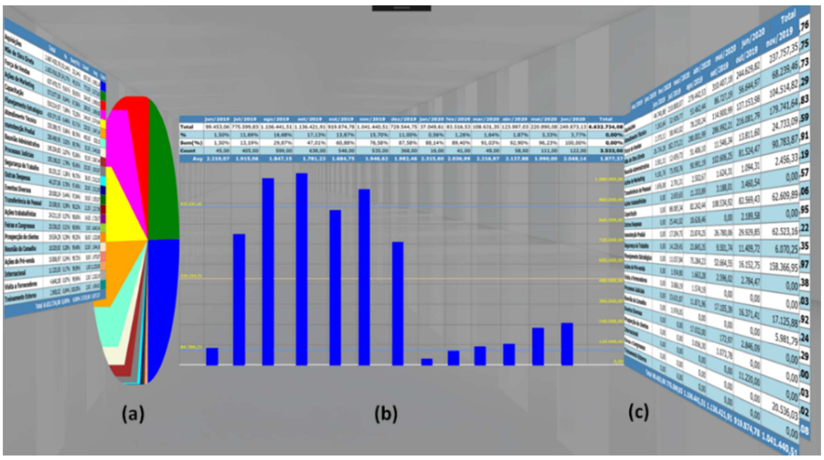

Figure 3. *(a) summary table and pie chart; (b) summary table and bar chart; (c) full table split into faces.*

As shown in figure 4, the split cube report placed in a side-by-side view highlights "outer columns." The outer columns generate the pie chart in figure 3 (a), while the outer rows produce the face in figure 3 (b) by applying the same criteria. Therefore, the outer rows and columns are the core information of the table, and they must appear as the "overview first" data.

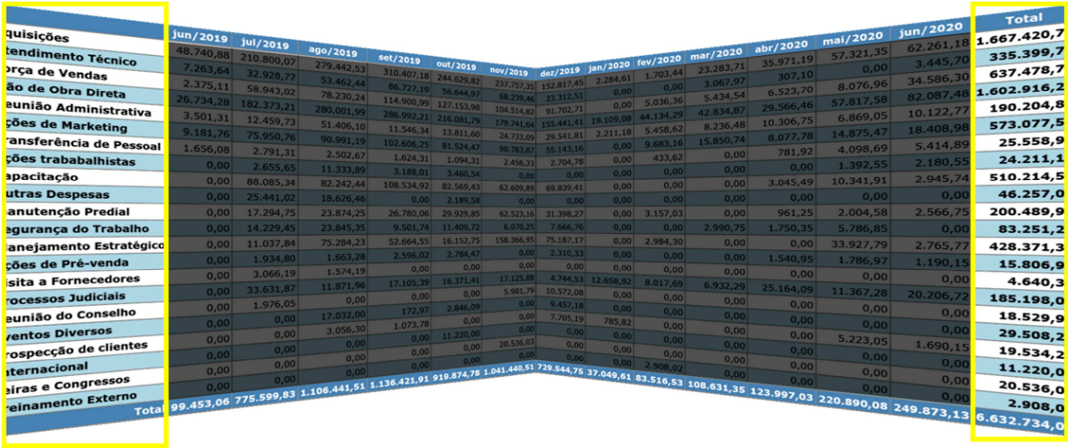

Figure 4. *Full table in a side-by-side view.*

The pie chart for columns and a bar chart for rows was just personal preference. The pie chart highlights the participation of each column in the result, i. e., treat columns as categories. However, row data are temporal, and the bar chart illustrates how numbers change over time. However, someone would consider the opposite a better approach: a pie chart to indicate progress over time and a bar chart to compare the participation in the categories. Otherwise, using the same chart type makes comparing row and column data easier. All of these scenarios are easily reached by replacing the content of the face or creating new faces.

From the insights provided by the overview faces, it is possible to generate segmented views as "zoom and filter." For example, figure 5 (a) shows a quarterly review (rows), while figure 5 (b) shows three selected categories. Calculations are made only for the selected set of data.

	jan/2020	fev/2020	mar/2020	Total	%	Sum(%)	Count	Avg
Aquisições	2.284,61	1.703,44	23.283,71	27.271,76	11,90%	11,90%	10,00	2.727,18
Atendimento Técnico	0,00	0,00	3.067,97	3.067,97	1,34%	13,24%	1,00	3.067,97
Força de Vendas	0,00	5.036,36	5.434,54	10.470,90	4,57%	17,81%	4,00	2.617,73
Mão de Obra Direta	19.109,08	44.134,29	42.834,87	106.078,24	46,28%	64,09%	53,00	2.001,48
Reunião Administrativa	2.211,18	5.458,62	8.236,48	15.906,28	6,94%	71,03%	8,00	1.988,29
Ações de Marketing	0,00	9.683,16	15.850,74	25.533,90	11,14%	82,17%	11,00	2.321,26
Transferência de Pessoal	0,00	433,62	0,00	433,62	0,19%	82,36%	1,00	433,62
Ações trababalhistas	0,00	0,00	0,00	0,00	0,00%	82,36%	0,00	0,00
Capacitação	0,00	0,00	0,00	0,00	0,00%	82,36%	0,00	0,00
Outras Despesas	0,00	0,00	0,00	0,00	0,00%	82,36%	0,00	0,00
manutenção Predial	0,00	3.157,03	0,00	3.157,03	1,38%	83,74%	1,00	3.157,03
Segurança do Trabalho	0,00	0,00	2.990,75	2.990,75	1,30%	85,04%	1,00	2.990,75
Planejamento Estratégico	0,00	2.984,30	0,00	2.984,30	1,30%	86,34%	1,00	2.984,30
Ações de Pré-venda	0,00	0,00	0,00	0,00	0,00%	86,34%	0,00	0,00
Visita a Fornecedores	0,00	0,00	0,00	0,00	0,00%	86,34%	0,00	0,00
Processos Judiciais	12.658,92	8.017,69	6.932,29	27.608,90	12,05%	98,39%	12,00	2.300,74
Reunião do Conselho	0,00	0,00	0,00	0,00	0,00%	98,39%	0,00	0,00
Eventos Diversos	0,00	0,00	0,00	0,00	0,00%	98,39%	0,00	0,00
Prospecção de clientes	785,82	0,00	0,00	785,82	0,34%	98,73%	1,00	785,82
Internacional	0,00	0,00	0,00	0,00	0,00%	98,73%	0,00	0,00
Feiras e Congressos	0,00	0,00	0,00	0,00	0,00%	98,73%	0,00	0,00
Treinamento Externo	0,00	2.908,02	0,00	2.908,02	1,27%	100,00%	2,00	1.454,01
Total	37.049,61	83.516,53	108.631,35	229.197,49	0,00%	0,00%	106,00	2.162,24

(a)

	Aquisições	Atendimento Técnico	Força de Vendas	Total	%	Sum(%)	Count	Avg
jun/2019	48.740,88	7.263,64	2.375,11	58.379,63	2,21%	2,21%	29,00	2.013,09
jul/2019	210.800,07	32.928,77	58.943,02	302.671,86	11,46%	13,67%	185,00	1.636,06
ago/2019	279.442,53	53.462,44	78.230,24	411.135,21	15,57%	29,25%	257,00	1.599,75
set/2019	310.407,18	86.727,19	114.900,99	512.035,36	19,39%	48,64%	331,00	1.546,93
out/2019	244.629,82	56.644,97	127.153,98	428.428,77	16,23%	64,87%	276,00	1.552,28
nov/2019	237.757,35	68.239,46	104.514,82	410.511,63	15,55%	80,41%	242,00	1.696,33
dez/2019	152.817,45	23.312,51	91.702,71	267.832,67	10,14%	90,56%	139,00	1.926,85
jan/2020	2.284,61	0,00	0,00	2.284,61	0,09%	90,64%	1,00	2.284,61
fev/2020	1.703,44	0,00	5.036,36	6.739,80	0,26%	90,90%	3,00	2.246,60
mar/2020	23.283,71	3.067,97	5.434,54	31.786,22	1,20%	92,10%	11,00	2.889,66
abr/2020	35.971,19	307,10	6.523,70	42.801,99	1,62%	93,72%	21,00	2.038,19
mai/2020	57.321,35	0,00	8.076,96	65.398,31	2,48%	96,20%	33,00	1.981,77
jun/2020	62.261,18	3.445,70	34.586,30	100.293,18	3,80%	100,00%	48,00	2.089,44
Total	1.667.420,76	335.399,75	637.478,73	2.640.299,24	0,00%	0,00%	1.576,00	1.675,32

(b)

Figure 5. *(a) Filter for quarterly review (b) Filter by category.*

3.3. Information Integration

Sometimes, users must analyze the same information through HyperBook, HyperRelation, and HyperAnalyzer with different perspectives. For example, video, voice, and music blended with text, graphics, and plain sheets in presentations based on a storytelling approach. Additionally, in traditional standalone applications, data files tie to one application at a time. Thus, the application must release the data file to avoid "share violation: another process might be using the file" operating system error.

Hypercube implements a repository called "data axis," in which workscenes access shared data files without causing such errors. When the user switches workscenes, the active one receives advice to update visual objects to reflect eventual changes.

4. Results

In the previous work, we presented a "preliminary assessments" section for the HyperBook workscene and its interface [24]. It involved general concepts, such as bindery, camera, and "depth and surface." Now, we believe it is fundamental to understand the users' feedback on the HyperAnalyzer workscene and, as such, conducted acceptability and usability tests with 26 participants. The goal was to evaluate 1) participants' adaptation to a VR-based interface, 2) visualization of the same data in different layouts, and 3) data comparison in parallel layers in the "depth and surface" way. HyperAnalyzer was used for 01 month in FACCACI faculty classes in parallel with other data analysis software.

The participants pointed out usability problems, bugs, and propositions, most of them solved during the test period. In the end, the participants filled out the evaluation forms. Tables 1 and 2 show the results.

Table 1. *Acceptability questions and scores.*

Question	Totally disagree	Disagree	Neutral	Agree	Totally agree
1) Adaptation required little effort	0	3	12	9	2
2) Keeping graphs and tables in the same environment favors concentration	0	2	9	12	3
3) The conceptual proposal adds value to data analysis, and I see the potential for expanding the tool	0	1	4	16	5
4) Visualizing the same data in different layouts (e.g., pie charts or bars) helps in realizing the numbers	0	3	4	13	6
5) Comparing data on different planes of the screen provides a better understanding of its context	0	0	4	17	5
6) Generating subsets of data (e.g., bimonthly, quarterly, half-yearly) makes the tool dynamic and flexible	0	0	3	19	4
7) The possibility of freely organizing the faces (graphs and tables) helps to evolve the analysis	0	0	3	15	8
8) Camera movements and the transition between faces (tables and graphs) help to hold the audience's attention if the prototype is used as a slideshow or to record a video	0	0	6	14	6
Total	0	9	45	115	39
Percent		4.33%	21,63%	55,29%	18,75%

We used IBM SPSS version 29.0.0.1® to evaluate the SUS scores [23]. First, the Kolmogorov-Smirnov test (KS) reached $p = 0.1045$ (i.e., $p > 0.05$), which revealed the possibility of at least one normal distribution. Therefore, we conducted parametric analysis through mean and standard deviation, as shown in Table 2.

Table 2. *SUS results divided into participants' profile.*

				SUS		
id	**Variable**	**Value**	**Participants**	**Average**	**Std Dev**	**Grade**
1	General	N/A	26	60.6731	11.8394	D
2	Age	18 to 24	22 (84,62%)	57.7273	9.5913	D
3	Age	*Above 24*	4 (15,38%)	95.6250	8.7464	A+
4	Gender	*Male*	14 (53,85%)	65.8929	11.5961	C
5	Gender	Female + not informed	12 (46,15%)	54.5833	8.8290	D
6	Education	*Administration*	6 (23,08%)	67.9167	14.4638	C
7	Education	Countability	20 (76,92%)	58.5000	9.9499	D
8	SO	Android	11 (42,31%)	57.7273	10.0258	D
9	SO	macOS / iOS	10 (38,46%)	59.7500	9.1822	D
10	SO	*Windows*	5 (19,23%)	69.0000	15.7797	C
11	Fluency	1 (beginner)	2 (7,69%)	55.0000	5.0000	D
12	Fluency	2 (beginner)	6 (23,08%)	62.0833	7.1322	D
13	Fluency	3 (intermediary)	4 (15,38%)	52.5000	9.1856	D
14	Fluency	4 (advanced)	7 (26,92%)	58.2143	9.6097	D
15	Fluency	*5 (advanced)*	7 (26,92%)	68.2143	14.7427	C
16	2021	*Yes*	9 (34,62%)	64.7222	13.3565	C-
17	2021	No	17 (65,38%)	58.5294	10.3277	D

The acceptability evaluation scored 74.04% of "agree" and "totally agree" against 25.96% of "disagree" and "neutral." There were no "totally disagree" evaluations. Previously, the HyperBook evaluation scored 81.05% of "agree" and "totally agree" and 18.96% of "disagree" and "neutral" [24]. The higher number of neutral scores in questions 1 and 2 would indicate that familiarity with the environment is an issue. Finally, the low number of "neutral" answers combined with no "disagree" for questions 5 – 8 may indicate good user acceptance.

On the other hand, the SUS evaluation scored 60.6731. In 2018, Lewis created a reference table mapping SUS score ranges to percentiles [23]. We added the "Grade" column in table 2 following that methodology. Indeed, the author proposes to interpret the SUS scores as 1) Worst imaginable = 12.5; 2) Awful = 20.3; 3) Poor = 35.7; 4) OK = 50.9; 5) Good = 71.4; 6) Excellent = 85.5; 7) Best imaginable = 90.9. Thus, after reviewing HyperAnalyzer according to Lewis' score, the result was "OK" for users in general and "best imaginable" for users above 24 years old.

5. Discussion

HyperRelational and HyperAnalyzer draw on core HyperCube model aspects and some specific features introduced in this article [24]. Traditional visualization systems are "single visualization oriented," i.e., they try to create the best visualization strategy possible, hoping it fits most users. HyperAnalyzer uses the "depth and surface" approach to allow Shneiderman's Visualization Mantra in parallel planes and avoid the "geometrical visualization" dilemma. Besides, new ways of grouping data allow a higher number of visualizations. Then, these possibilities link to each other as in a permutation game. Finally, "side by side comparison," cognitive physiology, and Tom's Information interaction process recommendations help validate the visualizations [46].

A typical data exploration starts by preparing it in HyperRelational, i.e., choosing one or more tables, combining, and filtering the data within them. For instance, to remove undesired columns, create relationships with other data sources, i.e., an open database on the web. Next, users mount dynamic forms in ShopWindow to "zoom-and-filter" information. If the table links to others, it is possible to explore related data in a "detail-on-demand" fashion. This approach would make it easier to validate data, even for non-technical users. Finally, users select columns to create a data cube in the HyperAnalyzer. In another scenario, users would need to explore the same table with different filters. Here, each filter occupies one face on a "side by side" comparison. Therefore, HyperRelational would be applicable in a data lake and similar exploration.

HyperAnalyzer handles multidimensional datasets as one or more 4D-hypercubes unfold into a set of three-dimensional sub-cubes [22]. Therefore, users can couple or divide data to reach the desired level of detail for the analysis taking a geometric shape as a reference. Consequently, it is applicable in general "big data" but also in "fast data" and "thick data" applications that can take advantage of this tool. Finally, the extra behavior of dynamic forms in HypeAnalyzer allows inspecting in detail the numbers that constitute one tuple.

The "depth and surface" technique helps users realize the precedence of information, as it occupies different layers. Besides, layered-organized data reduces the cognitive load of switching from one view to another and working memory usage, aiding users in analyzing data and obtaining insights. Finally, it is a trend to share the screen in online meetings and presentations or record it to create a video. Therefore, HyperCube4x is ready to be a data presentation software.

Finally, Kortum and Bangor (2013) published a SUS rating table of the overall experience from a survey where 866 participants scored Excel 56.5 [21]. Once HyperAnalyser is a data analysis software, Excel is the nearest reference presented in the list. Therefore, the benchmarking between HyperAnalyzer and Excel suggests that it was a good assessment as a starting point.

6. Conclusion and Future Work

This article introduced the aspect of the hypercube model oriented to exploring and analyzing data 1) Geometrical visualization; 2) mapping relationships among information as spatial dimensions. We also demonstrated using "compare side-by-side" and "depth and surface" techniques and how they fit Shneiderman's visual-information-seeking mantra applied to data exploration and analysis. Results highlight the users' positive feedback and experience regarding the HyperAnalyzer workscene. We even indicated that users above 24 might prefer this interaction metaphor, as they scored the workscene as "best imaginable" in the final questionnaires. The next step to complete the "tour" around the HyperCube model's core aspects is evaluating HyperRelational as a standalone WorkScene. Then, to assess the synergies among the three WorkScenes and HyperCubeScene, the management workscene. In addition, the WorkScene HyperBook awarded 02 government incentive funds to develop market-oriented projects. We intend to publish the results related to these projects as soon as they are available.

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