Mapping Context-Dependent Dimensions of Human-Data Viz Interaction

Sara Beschi[0009−0006−4969−6565] and Angela Locoro[0000−0002−6740−8620]

Università degli Studi di Brescia, Dip. di Economia e Management, Italy
{sara.beschi,angela.locoro}@unibs.it

Abstract. This paper attempts to identify and characterize some context-dependent dimensions of Human-Data Visualization Interaction that are crucial to estimate the complexity of data-driven decision making. These dimensions are only partly related to off-line considerations such as the kind of charts, the data represented, and the like, and are mapped with operationalization constructs for their characterization and assessment. A what-if scenario in an industrial company is the starting point to reflect upon living constraints, such as the level of expertise in visual analytics of managers (the so-called Visual Information Literacy), the strategy that drives the decision process, and the flexibility and adaptability of the technology design to the data characterizing the decisions and both the previous aspects. How can we relate these three aspects for a better estimate of the data-driven decision-making flaws and complexity? Some hypotheses are proposed here.

Keywords: Data Visualization · Visual Information Literacy · Human-Data Interaction · Evaluation Methods · Pragmatic Framework.

1 Introduction and Background

Enterprises are increasingly immersed in the data-driven revolution and need to align with innovative corporate process management. This change is closely related to the fast development of big data technologies, the imperative for digital transformation, and the vast volume of data that companies have access to [20]. Data analysis offers a new opportunity to uncover hidden values among the vast array of available information, improve understanding of business processes, develop predictive capabilities, and facilitate issue detection.

The use of information and data through the adoption of Business Intelligence (BI) and Analytics systems yields *Business Value* in Organizations, directing processes towards increased productivity, enhanced decision-making efficiency, and deeper insights into customers and markets to foster innovation. This corporate value translates into tangible performance enhancements, such as cost reduction, identification of growth opportunities, and maintenance of competitive advantage in the market [10].

To effectively measure *Business Value* and the impacts arising from the adoption of these systems, it is important to predict and identify the various professional roles and competencies necessary to grasp the business context, formulate

suitable analytical solutions and data visualizations, understand data sources and data formats, and be familiar with data collection and transformation systems [8].

These professional figures, dedicated to uncovering the most significant insights, emerge as key users of Data Visualization systems. Throughout their interaction, various factors impact the analysis activity and subsequent interpretation of results.

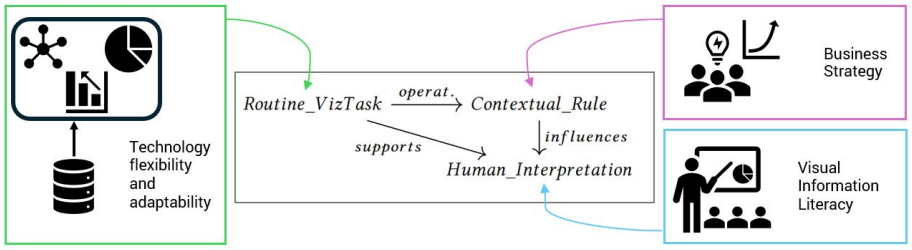


Fig. 1: The diagrammatic sketch of a pragmatic framework for human-data viz interaction at the center of the figure was proposed by one of the authors in [7] (the abbreviation "operate." stands for "operationalizes"), and extended with the current hypothesized dimensions (Technology flexibility and adaptability; Visual Information Literacy; Business Strategy) emerging from and applied to a Business Case.

These factors not only concern the type of visualization presenting the data, but also how the professional figure reads and interprets the charts, their familiarity with the system, their approach to daily professional practices, and the impact of context and experience on the decisions and questions arising during data analysis and *Business Strategy* definition.

This work contributes to the Human-Work Interaction Design (HWID) domain by investigating how users interact with data visualization tools within specific organizational contexts. Aligning with HWID principles, our framework emphasizes the socio-technical interplay between user skills, tasks, and system usability, providing a structured approach to understanding these interactions.

In our previous work, presented at AVI in 2020 [7], we introduced a pragmatic framework for Human-Data visualization interaction [21], which we report in the center of Figure 1. This schema aimed at capturing, from a category-theoretic perspective, structural elements and their structure-preserving interactions during data visualization activities in the wild.

From this schema, it was clear that each interaction property should be contextualized, and different "concretions" can emerge among the elements of the framework. For example, the same Data Visualization may be interpreted differently, based on the task, the role, and the background knowledge of the user interacting with it. The same task may include the interaction with very differ-

ent, sometimes opposite, data visualizations, depending on the rules that each organization has for defining their routine interactions with data and, again, based on the level of expertise of its members. The three dimensions of the framework—Technology Flexibility and Adaptability, Visual Information Literacy, and Business Strategy—are interrelated. While each dimension addresses a distinct aspect of Human-Data Visualization Interaction, their interdependence becomes evident in practical applications. For instance, usability (linked to Technology Flexibility) must account for user needs, abilities, and expertise, which are inherently tied to the context and task at hand (Visual Information Literacy). Furthermore, usability is closely related to data complexity, as more complex data requires interfaces that enhance interpretability without overwhelming the user. To clarify the first dimension, Technology Flexibility and Adaptability refers to the system's ability to accommodate varying levels of data complexity and user expertise. This includes features like customizable visualizations, interactive elements, and adaptive feedback mechanisms that adjust to user behavior and context. For example, in scenarios involving high data complexity, the system should provide advanced filtering and drill-down options to facilitate sense-making for experienced users, while simplifying views for less experienced ones. Other studies in the same domain [5] witnessed and highlighted the consolidated importance of characterizing and strengthening the connection between visualization tasks and data management optimization techniques, hence developing research directions for visualization interactions and optimization techniques for data management. The major gaps that 30 years of studies explored with the above review let emerge were related to the lack of mechanisms in data visualization interactions to:

- provide semi-automatic means to visually encode data, especially in routine data analysis
- allow the annotation and labeling of visualizations, in order to improve sense-making, intra-personal and inter-personal communication
- recording the interactions with data visualization, to enhance longitudinal patterns finding among other dimensions that are related to history of interactions

In the present study, we want to reinforce this framework in two directions: the former is to show its instantiation through a business experience made by one of the authors, which allowed the translation of some structure-preserving relations of the framework into accurate what-if analysis dimensions of interactions in the company (Section 3); the latter aims at mapping the theoretic dimensions of our framework into context-dependent ones, emerging from the concrete case explained, to characterize measurable constructs (Section 4).

Mapping this framework with concrete dimensions, and illustrating an example of a *Business Scenario*, we highlight the significant influence of the following factors on data interpretation and the resulting *Business Value*: interaction with data visualizations, experience with the system, and the business context.

2 A Business Scenario Context

Among the various data-driven decision-making processes that emerge in the business context, one of the key sectors is marketing. Specifically, *Customer Relationship Management* (CRM) systems represent a fundamental data source for generating value from customer information. Effectively leveraging this data can provide meaningful insights into marketing performance, enabling marketers to optimize campaigns, increase sales, enhance customer engagement, and improve relationships with customers to better meet their needs [1].

The various widely used CRM systems in the market offer a range of tools for chart creation and data exploration. This enables the development of dashboards that provide marketers with a constant overview of key indicators derived from data sources such as social media, website interactions, sales, and email campaigns.

Depending on marketers' level of experience in using the systems, they can create increasingly sophisticated visualizations, starting from simple metrics like click-through rates and conversions, all the way to customer segmentation. This enables them to extract increasingly detailed information, which can then be transformed into targeted and strategic actions.

An example of using data analysis tools integrated into the CRM could involve monitoring marketing campaigns. To assess their effectiveness, measures such as conversion rates, click-through rates, and revenue generated are utilized. This approach allows for the rapid identification of less effective campaigns and enables data-driven adjustments to optimize performance.

The presented scenario focuses on a real-life case where professionals interact with these systems to address a business question. We will see how users' level of experience and the type of visualization chosen to represent performance metrics significantly influence the level of understanding and analysis of the data, as well as the overall experience quality.

3 A What-if Business Scenario From Observation of Business Practices

Alpha Manufacturing is a manufacturing company based in Northern Italy, specialized in the production of consumer goods. Alpha Manufacturing is focused on improving *internal data analytics*, with a focus on *marketing campaigns performance*. During the direct observation of business activity by one of the authors, the what-if user scenario named "Unexperienced User with Complex Graph and First Interaction" was identified. In this scenario, User1 had no experience with the system but she was a domain expert, and she was asked to answer a question: *"What is the impact of our latest marketing campaign on customers?"*. User1 was interacting with the CRM dashboard and came across a three-dimensional scatterplot showing email open rate concerning variables such as the day of the week, time-sent stamp, and content type (Figure 2a). She had many interpretation difficulties. These were related to understanding the meaning of the

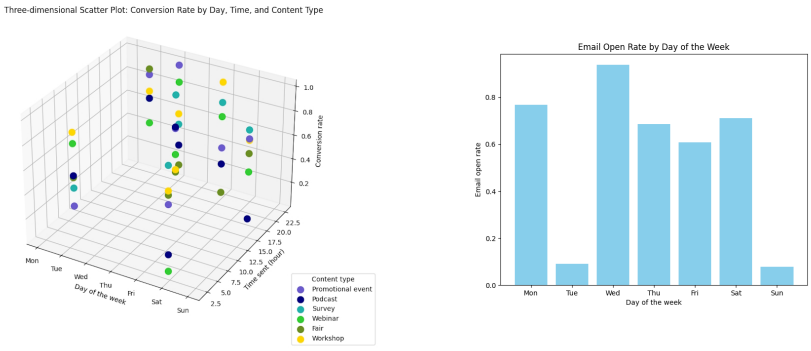
three-dimensional graph, also due to the lack of suggestions from the interface on how to interact with the graph, which further confused her.

A second observation during a routine activity brought to identify the second what-if user scenario named "Expert User Scenario with a Simple Graph as First Iteration". Here, User2 was a system and domain expert, and should answer the question: *"Which user segments showed the most engagement in the latest marketing campaign?"*. Interacting with a chart as simple as the one required by User1 limited User2's initial interaction experience, as she wanted to derive detailed information where she had only bars showing email open rate by day of the week (Figure 2b). The interpretation difficulty lying in the current interface did not allow User2 to explore specific details or identify relevant customer segments. The methodology used to develop the framework involved direct observations in business scenarios, focusing on capturing user interactions and challenges in real-world contexts. The observations were conducted through direct monitoring of user interactions within a CRM environment. Data were collected using think-aloud protocols, where participants verbalized their thought processes while navigating the system. This method provided insights into their challenges and decision-making strategies, revealing usability gaps and areas for improvement in the design of complex visualizations. For example, the "Inexperienced User with Complex Graph" scenario emphasized the importance of adaptive interfaces and usability in systems, while the "Expert User with Simple Graph" scenario highlighted the need for custom tools tailored to varying levels of VIL. Future studies could incorporate controlled experiments or surveys to validate these findings and further strengthen the framework's empirical foundation.

4 Mapping the Three Dimensions to the Pragmatic Framework and Characterizing Them

Once recognized that concrete dimensions exist and are mappable in our framework, there is the need to characterize and operationalized them. Some hypotheses of how to characterize them and assess them are outlined.

Usability, never too much Usability! The visual inspection step above is an instantiation of the *Routine_ VizTask* structure of our framework, which concerns the need to interact with data visualization *Technology* that (should be) flexible and adaptable enough for doing visual analytics as often as the user's role may require. Characterizing this context-dependent dimension means providing evidence of the users' difficulties in the scenarios depicted, in terms of usability of the data visualization interface. This may have led to introducing explanatory feedback making sense of each element for User1 scenario, which may have improved the experience of User1 with the Data visualization system. For User2, an advanced control panel may have allowed her to select and combine dimensions to create custom views. Drill-down tools may have let her explore specific details without losing the big picture. Advanced filters may have allowed User2



(a) An example chart similar to the one utilized in the what-if user scenario titled "Unexperienced User with Complex Graph and First Interaction".

(b) An example chart similar to the one utilized in the what-if user scenario titled "Expert User Scenario with a Simple Graph as First Iteration".

Fig. 2: In the What-if Business Scenario two different data visualizations are involved, both aimed at representing frequent measures of interest in the analysis of marketing campaign performance.

to apply specific conditions to isolate relevant data, optimizing the process of finding specific segments of users. Besides the need to assess usability through traditional tests to measure interaction efficiency, an open challenge may be how to relate usability to the user's behaviors need that depend on the level of literacy and expertise in routinely using data visualization. Going beyond usability has been advocated in other domain such as the EUD one, where the notion of EUDability came to the scenes [4] and new assessment dimensions were devised. As affirmed by studies on data visualization usability [5] [7], it is evident that a data visualization interface is a specific kind of interface, whose "ability to be used" depend on at least two dimensions: the *complexity* of the data and its *interpretability*, e.g., the difficulty of the data and the ability of the user [17]. The former can be strictly related to the query posed by users upon the data and, hence, to the data complexity. A classification of data properties contributing to their complexity is depicted in Figure 3, where each single dimension of complexity is put in relation with the others, and an order of magnitude of complexity is emerging from the picture.

For example, if data are composed of multiple entities (e.g., thousands of e) and each entity have multiple properties (e.g., tenths of p) of multiple data type and aggregation type, the order of complexity would be maximum, e.g.,

$$O(|e| * |p| * |type| * |aggr|) \tag{1}$$

would be the magnitude of the complexity to keep into account.

The complexity of the data raises connected problems of:

– what are the best visualization that enact sense making for data with those characteristics
– what is the best interaction that should be provided with data of such complexity
– what is the level of expertise of the user for data of such complexity and what are techniques to simplify the complexity and optimize understanding

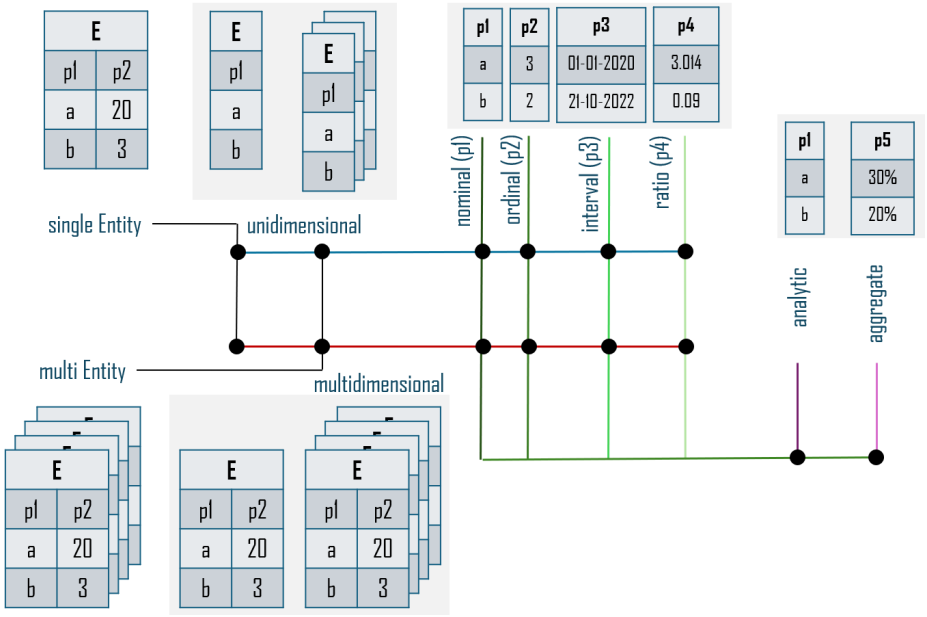


Fig. 3: The schematic overview of how complexity can be seen as a multi-dimensional construct, where each dimension (entity dimensionality, type of data, type of aggregation) belongs to data properties $(p_1, p_2, ..., p_n)$, and the complexity of data emerges as an "operationalization" of data characteristics and number of dimensions, through an order of magnitude of complexity that grows as the number of data properties grow.

Assessing the Visualization Literacy of Individuals. The visual inspection should boost the *Human_ Interpretation* of the data at hand to answer the questions about the marketing campaigns. This step regards the second structure in our framework. The context-dependent characterization of this dimension may concern the *Visual Information Literacy* of the user, besides her domain of expertise. Visual Information Literacy has been defined as "the ability to properly process information related to data graphics, i.e., encoding information into data graphics and decoding information from data graphics" [18].

The importance of characterizing conceptual and practical skills in data visualization stems from the fact that this ability is deemed as crucial as textual literacy and numeracy. Many challenges arise from the need to characterize Visual Information Literacy of individuals. For example, the "information" aspect is a challenging one, in that what and to which extent the informational aspects should be considered in the definition of individual skills is far from being clarified. This issue points to the need to consider whether to include in the Literacy also the abilities to work well with information sources, using strategies to locate, compare, evaluate, organize, apply, and synthesize data, to communicate, explain, and instruct people about abstract concepts and ideas towards constructing new knowledge, understanding and refining communication skills.

Some main stances in characterizing Visual Information Literacy regard:

1. The identification of dimensions in data graphics
2. The description of Visual Information Literacy skills in individuals
3. Methods to assess Visual Information Literacy
4. Practical solutions to adjust visual communication to the skills of individuals

The first point has been addressed in the section on usability, where the concept of complexity of data dimensions was explored and depicted in Figure 3.

An example of Visual Information Literacy characterization and assessment was given in [18]. The model of Visual literacy presented in this paper consists of six cognitive levels, which are seen in progression, from the first to the last one, as an evolution of people's skills in reading and interpreting graphics. The model was partly borrowed by models of text reading skills, where each level is characterized by specific skills that are preparatory to acquiring the skills of the next level. The model for visual literacy skills includes the following levels:

1. Map: basic recognition of syntax elements in data graphics.
2. Integrate: relate visual elements to form a coherent semantic understanding of the graphic.
3. Compute: quantification of relationships within the visual data (e.g., computations over numerical data).
4. Reason: draw conclusions based on visual information.
5. Infer: add new knowledge to proper beliefs from the data.
6. Explain: provide rationales for the design of data graphics and exhibit critical thinking skills about the efficacy and the effectiveness in conveying information.

As said above, the model showed a progressive increase in complexity at each level. Participants' ability to correctly interpret data graphics decrease as the complexity of the visualizations increases. The study in [18] found that the levels of the designed model align well with the participants increasing cognitive demands. Simple visualizations were processed more accurately than complex ones, with a higher rate of correct answers for lower-level tasks.

In the current scenarios, for example, where the User1 Visual Information Literacy is scarce, replacing the graph with a bar graph that shows the email

open rate by day of the week, may have facilitated User1 in identifying the days that registered the highest email opening rate and obtain an immediate indication of the positive or negative impact of the campaign on the various days. User1 may have found the new interface more accessible and may have become capable of answering her questions more efficiently, improving her confidence in analyzing marketing data.

An improved experience for User2 may have taken into account her higher Visual Information Literacy, and the full advantage of the complexity of an advanced graph, able to answer her analytical questions quicker and more thoroughly and, overall, improving her marketing data analysis experience. For example, a more complex chart such as an interactive heatmap may have improved the visualization of customers engagement based on demographic (age, gender, geographic location), behavior (frequency of interaction with emails), and temporal variables. This new view may have given User2 the ability to customize data presentation and explore specific details.

Besides models of visual literacy like the ones presented above, there are new scenario of research that try to go beyond rigid constructs for characterizing visual literacy to appeal to contextual evidences [14]. Starting from the considerations that various aspects of visual literacy were already targeted, what is yet to be fully captured is how define, study, and improve visualization literacy with the lenses of measurement, interventions, and pedagogy.

In the scenarios above presented, we need to cope with two different kind of literacy: the one acquired in the past, which can be based on previous learning and education curricula, and can be thought as a quite standard baggage of notions; the one acquired during individual experiences of tools, interfaces, visualization kinds, and ways of more or less creatively re-combine the knowledge acquired into new, creative and personalized practices (e.g, pragmatic knowledge in the domain of semiotics seeding and re-seeding of experiences and knowledge, see for example [9, 12]). We need to keep into account, in the words of [12], that "evolutionary processes [...] are determined through an iterative process of collaboration among multiple stakeholders, rather than being completely specified before system development occurs; they must evolve because they cannot be completely designed prior to use; they must evolve to some extent at the hands of the users, and; they must be designed for evolution".

Tracing the Behaviors of Users. The visual inspections step also supports a precise *Business Strategy*, which is concretely rendered as highly-customized query related to the marketing campaigns. This step may be seen as an instantiation of the *Contextual_Rule* in our framework. This third context-dependent dimension may be characterized as the capability of the Data Visualization to reflect the users' strategies. In terms of interactions, these strategies concern the two aspects outlined above: the information quantity (complexity) contained in the data and the users' behavior (interpretation) during interactions with visualizations [11, 16]. The former requires a classification of data visualization information from the least to the most complex, depending on the number of entities represented in the data, the number of properties depicted for each entity, the

type of data of each represented property (being nominal, ordinal, numeric discrete, and numeric continuous), and the level of details (e.g., aggregated or not aggregated) [15].

Analyzing users' systematic behavior can help identify the areas of interest they focus on, based on their confidence with the visualization, their current strategy, and their literacy level. Recurring interaction patterns often emerge, shaped by these factors. For instance, users with higher Visual Information Literacy tend to leverage advanced tools and techniques, as demonstrated in our case studies. This identification is essential for acquiring knowledge of data more effectively and efficiently, and for providing a more customized experience. Furthermore, behavioral aspects in users depend on related concepts such as literacy level, usability of the tools, and complexity of the data. In line with the sociotechnical approach to Human Computer Interaction, it is essential to consider both technical and social factors in designing interactive visualizations, as this dual perspective facilitates a more contextual analysis of user behavior and interaction [2]. This higher level of customization may be reached, for example, by tracing users' behaviors with Data Visualizations in search of systematic biases or recurrent patterns of visual analysis. Some tools already exist for exploration paths and analytics history storage [13] [19]. Assessing the information complexity, the usability, and the literacy of individuals for comprehending the users' behavior may advance data visualization tools. These tools may reach a personalized level such as being able to formulate on-the-fly query-answering and personalized charts interactions that could improve both the *Business Strategy* requirements and the *Human-Interpretation* aspects.

5 The impact of Augmented Analytics and the Quest for Explainability

The challenges observed in user interactions, such as the need for adaptive interfaces and better interpretability, highlight the importance of integrating advanced tools like Augmented Analytics (AA) and Explainable AI (XAI) to bridge usability gaps and enhance decision-making processes. In recent years, BI software has integrated Artificial Intelligence (AI) into various functions, leading to the rise of Augmented Analytics (AA). This approach combines machine intelligence with human intuition to accelerate insights, uncover discoveries, and enhance data literacy across organizations [3].

The integration of AA introduces a significant opportunity to enhance both the usability and interpretability of data visualizations within BI systems. By automating insights and providing explainable outputs, AA can supports users with varying levels of VIL in understanding and leveraging complex data.

While some AI applications are fully automated, complex business problems require human involvement. AI enhances human-machine collaboration, surpassing individual capabilities, facilitating modern analytics for different types of users, and increasing confidence in outcomes.

AA systems are significantly transforming BI software by integrating AI, fundamentally changing how users interact with these advanced tools. This integration leads to a drastic shift in user interaction, necessitating new skills to utilize the enhanced features effectively [6]. Some of the main features are:

- Facilitating smart discovery by assisting managers and analysts in generating automated insights directly within the dashboard;
- Automating and guiding data preparation, transformation, and integration, thereby minimizing manual effort and expediting the analysis process;
- Enabling users to easily create charts, visualizations, and dashboards for quick and efficient preliminary data exploration;
- Allowing users to ask questions in plain language through natural language interaction, making data analysis accessible to users of all expertise levels, automating routine tasks, and freeing up human resources;
- Empowering users to incorporate complex analytics into their decision-making processes through Automated Machine Learning;
- Accelerating the analysis process and uncovering hidden patterns through automated data analysis and anomaly detection, providing valuable insights for process optimization;
- Enabling agile decision-making through real-time data processing, allowing businesses to respond swiftly to changing market conditions and emerging trends;
- Integrating tools for analyzing and visualizing unstructured data such as social media, news, and cyber intelligence.

Utilizing AA significantly enhances sustainability across various industries. For example, automating data preparation, data analysis, and reporting, reduces the need for extensive manual data handling, minimizes resource consumption, reduces costs, helps to make predictions and anticipate phenomena, and saves valuable time for analysts and managers allowing them to focus on strategic activities. The proposed framework also aligns with sustainability goals by promoting efficient use of data visualization tools. Simplifying user interactions reduces cognitive load and resource consumption, while fostering a better understanding of complex data ensures informed and sustainable decision-making.

While current research has highlighted the benefits of AI-powered insights and automation, the ways in which users interact with these advanced tools require further investigation. Understanding how different user roles and skill levels impact interaction with enhanced BI systems can reveal crucial insights into user adoption and satisfaction. Additionally, examining contextual factors, such as organizational culture and industry-specific challenges, can provide a more complete understanding of how these platforms can be optimized to meet different user needs.

5.1 Explainable AA and Visual Explanatory Information

There remains a need for a more in-depth exploration of the implications of user interaction with these systems. AA raised the problem of explainability of

AI and visual explainability. Both are crucial in the user scenario that we were analyzing and are considering for improvements.

AA systems are now integrated in various scenarios, where their decisions can have profound impacts on human lives. Despite their success, one of the critical challenges their "black-box" nature, which makes them nor transparent nor fully understandable. The need for explainability should become a major concern in the development of AA models. Transparent and interpretable models are essential for fostering trust in AA, ensuring fairness, and facilitating accountability. The field of Explainable Artificial Intelligence (XAI) aims to address these concerns by creating models that not only perform well but also provide understandable explanations for their decisions. This is particularly fitting the problem of providing the right degree of usability, understandability and explainability that enterprises stakeholders need to trust and evolve with the use of tools for supporting decision making.

By providing reasons or explanations for the decisions made by AA models, users can develop trust in the system. If users understand how a decision was made, they are more likely to trust its outcome, which is especially important in high-stakes fields such as healthcare, finance, or autonomous driving. Trustworthiness of models is a crucial goal of explainable AI, as it enables both technical and non-technical users to gain confidence in the system's outputs.

Explanations help users, particularly those affected by the AA's decisions, engage more with the process. Users can assess whether a decision is justifiable and align it with their expectations, leading to more informed decision-making. This is important in applications where user interaction with the AA would benefit by more user engagement, such as decision support systems.

Explanatory information enables users to assess the fairness of AA models. By understanding how inputs are processed to produce outputs, users can spot potential biases or unethical decisions. Fairness and ethics are vital for ensuring that AA does not perpetuate discrimination or other unfair practices.

Explanations lower the barrier for non-expert users to interact with and utilize AA systems. By making the internal workings of models understandable, XAI can help product owners, managers, and non-technical users leverage AI without needing deep technical knowledge, hence improving accessibility. For example, interactive explanations within dashboards can help non-expert users like User1 decode complex visualizations, while expert users like User2 can leverage advanced features to drill down into specific insights, enhancing their strategic analysis.

In an interactive workflow, explanatory information can guide users toward refining models. For developers, understanding how a model behaves in different scenarios can suggest ways to improve performance. Providing transparency through explanations allows for better refinement of the AI systems, particularly when users can see how different inputs lead to various outcomes.

Interactive refinement and optimization are an outcome and a goal of better visual interactions, and open challenges are those which address these new topics

emerging with the possibility of introducing aware and trustworthy AA tools into the visual analytics routines.

Visual explanatory information may enter this picture by:

- providing a system for interactive visualization with visual feedback and explanatory annotations;
- providing a system of diagnosing automatic decisions, visual feedback and exploration of complex reasoning by machines and identification of relevant points, nodes, or features for the decision made;
- allow higher-level abstractions upon algorithms and data, in order to interpret even more complex patterns in data, identify which data properties impact more on observed outcomes and
- tracking the interaction history and the data provenance, as well as tracking the visual explainers used. In this way a log of insights and findings may help refine and optimize models and decisions based upon them.

6 Addressing Limitations and Expanding Applications

The proposed framework has successfully outlined key dimensions of Human-Data Interaction, yet certain practical limitations highlight opportunities for further development. One pressing challenge is balancing the complexity of visualizations with their usability, particularly for non-expert users. Although advanced tools offer powerful insights, they risk alienating users with lower levels of VIL. To address this, future studies could explore interaction designs that adapt dynamically to user expertise, leveraging modular interfaces or customizable levels of detail to cater to diverse user groups.

Another critical limitation lies in system scalability and workflow integration. As datasets grow in size and complexity, ensuring the framework's adaptability across industries and organizational contexts becomes crucial. Future work could investigate approaches to optimize data handling, such as integrating cloud-based analytics or developing AI-driven tools that streamline workflows without compromising performance.

Beyond marketing and CRM scenarios, the framework's adaptability to other industries offers an exciting avenue for exploration. For instance, in healthcare, the interpretability of clinical dashboards could support timely and accurate decision-making, while in finance, adaptive visualizations could enhance real-time investment analyses. These domain-specific applications may reveal unique challenges, such as the need for higher granularity in data interpretation or stricter usability requirements, thereby enriching the framework's versatility.

To advance this field, establishing standardized evaluation methods for dimensions like VIL, usability, and complexity is essential. Future research should aim to design context-specific tasks and metrics that assess user interaction across varying domains, ensuring consistent benchmarks for system performance.

By addressing these challenges and broadening its applications, the framework can evolve into a robust tool that supports diverse industries, offering a foundation for more intuitive and effective Human-Data Interaction systems.

7 Conclusion and Future Work

Context-dependent dimensions of Human-Data Interaction are related to individuals and their tasks, role level, and tools usability dimensions composing the environmental conditions where big data interpretations and decisions based upon them take place. Despite the desire to provide timely and useful information, there are still gaps in technology design and margins for improvement in their intrinsic quality and in the quality of communication through them.

A dedicated study on this matter would give the possibility of characterizing and assessing the main dimensions of Human-Data Interaction with the aim to:

- identify the nature and the complexity of problems and data underlying the solution of problems through visual analytics practices and explanations;
- identify criteria of rightness of information visualization with respect to the Visual Information Literacy of individuals, in combination with further dimensions such as the data to be represented, the decisions to be made, and the context of information (routine, critical and fast, strategic, and the like);
- investigate the interaction dynamics and properties of visual tools for the proper communication of data, towards the identification of high-level requirements for their effective and efficient design;
- provide suggestions to the design, customization, and adoption of visual information systems for visual analytics and comprehension of big data in new and emerging data-driven scenarios in organizations
- let visual explanatory information become one of the major issues when AA tools are pervading the routine practices of analysis, prediction, and understanding of business trends, processes, and strategies

Mapping hypothesized dimensions with their operational counterpart may bring light on how to boost the business processes and practices towards a more aware and sized use of big data, and on how to improve the daily practice of people in different work scenarios, still providing a rigorous method of investigation through and decision driven by data.

Artificial Intelligence may support the process of providing customized data visualization as long as the context of practices becomes routinized and well-defined patterns of visual analytics and users' behavior are identified. For example, users' profiles may be designed and prompted by the AI to obtain different visualizations for the same dataset, depending on constraints about the role, task, and visualization literacy levels of individuals. Practices of explainable AI and AA may become routine tasks supporting trust and transparency, and may benefit from the visual means to become part and parcel of the visual analytics related to business.

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