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HOW TO EFFECTIVELY USE INTERACTIVITY WITH INTERACTIVE DATA VISUALIZATION ON GROUPS WITH DIFFERENT LITERACY LEVELS

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Project Work presented as partial requirement for obtaining
the Master's degree in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

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ABSTRACT

Open data can be used as an empowering tool to society; however, it is not usually accessible to the general audience. This difficulty tends to increase as users lack data literacy. Interactive data visualization is a solution to provide clearer information, enhancing understanding and engagement. This study aims to develop interactive visualizations with open data to understand how to effectively communicate a message. The prototype was created with Microsoft Power BI and the database was developed by The World Bank. This work contributed with a methodology to evaluate literacy and to evaluate the prototype with quantitative and qualitative metrics. ANOVA single factor tests pointed statistically significant differences between groups regarding accuracy, complexity, and comprehension. This suggests that data literacy should be considered when creating visualizations, and projects as DATALIT are essential to enhance users' literacy. Both groups agreed that the best visualizations were the bar, line and pie charts, and the choropleth map was well accepted. The least preferred visualization and the most complex was the bubble chart. Non-Experient users found the elements a little more complex. Both groups worked well with filters and slicers, and tooltips had a good acceptance. Groups considered animation the worst component. When the interaction was not described in the text, the Non-Experient group had more difficult in discovering it. Participants showed average good results in all measures, thus Microsoft Power BI is a useful tool to create effective interactive visualizations for different groups. The results from this work will allow organizations to understand how to adapt their visualizations to different audiences and the importance of data literacy skills.

KEYWORDS

Data Visualization; Open Data; Interaction; Data Literacy; Interactive Visualization

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1. INTRODUCTION

1.1. BACKGROUND

The growth of the Internet and communications, along with the expansion of its access, allowed the publication and use of open data to enhance transparency, public engagement, relations between governments and citizens, and enhance development and innovation in a wide range of fields (Gebre & Morales, 2020; Craveiro et al., 2016, Chua et al., 2020). Nowadays, nations as Canada and the European Union have as a political priority the open data movement. Open data resources can be described as public sector information made available free of charge for public use through government and public sector entities. Overall, open data is expected to improve the decision-making of both governments and individuals (Gebre & Morales, 2020; Blascheck, 2019; Jetzek et al., 2014).

Open data is usually employed by technical users, such as government agencies and non-governmental organizations. However, it is also useful for third-party private intermediaries whose goal is to take advantage of data to create new solutions (Chua et al., 2020). At the same time, open data can also be of worth to non-technical users, as the everyday citizen. In this case, open data promote citizen engagement and collaboration with the government in the process of addressing community needs. It also has an important role in improving public sector transparency, while being reliable, easy access, free of charge information (Chua et al., 2020; Gebre & Morales, 2020).

Yet, as stated by Gebre & Morales (2020), the availability of open data does not guarantee usage and critical engagement among the public. The authors affirm that, currently, the use of open data is generally low, and usage is often limited to researchers, data scientists, and professionals in the private sector. The authors identified two challenges concerning the use of open data by the public: (1) organization and presentation of data and (2) lack of data literacy skills. Open datasets usually are provided as spreadsheets and CSV file formats, with limited metadata, context, and data collection information. Moreover, there is no explanation of possible uses of the resources. Plus, the design of open data does not consider the fact that various groups of users process and use data to serve different purposes. Besides, the general audience usually does not have the means or skills to access, explore and understand data (Ruijter et al., 2017; Gebre & Morales, 2020; Blascheck et al., 2019).

An example of an open data provider is The World Bank (TWB). TWB is a renowned institution that offers open datasets as a source of information and as a tool to aid decision-making in public policy creation, for audit purposes, and to offer inputs for other global analysis. One of the databases developed by TWB is regarding their lending assistance for international projects. In this database, it is possible to understand how the monetary assistance from TWB is being applied worldwide and what issues are mostly addressed. It is also possible to use this information to perform an audit of TWB works and to evaluate if the institution is faithful to its mission, for example.

In this context, an interesting approach to make this increasing amount of open data more accessible is via web-based interactive visualizations (Blascheck et al., 2019). Data visualization and interactivity play a crucial role to enhance the comprehension and communication of data, attract user's attention, or

present success and progress data for society stakeholders. Data visualization is also a powerful tool for data democratization (Alexandre, 2016; Chevalier et al., 2018; Lee et al., 2020). Interactivity has the main purposes of (1) make the data more engaging or playful and (2) showing the data in manageable portions, facilitating both the understanding and the analysis of data, because the degree of complexity is reduced. Then, users can explore all information and independently find answers to their questions (Figueiras, 2015).

It is important to attempt to the user's ability and confidence in understanding data visualization tools. This can be assessed through the user's visualization literacy level, or the ability to use visualizations to interpret visual patterns and extract or manipulate information. Visualization literacy is a concept that also embraces perceptions of data, information, and digital literacies. Together, all these abilities are responsible for empowering citizens to make better-informed decisions in everyday and community life. However, not all citizens are already literate or are even aware of this concept. Projects as DATALIT, hosted by the European Commission, are being developed aiming to spread the importance and challenges of data literacy, and develop competence-oriented learning modules to enhance literacy in higher education and business. Thus, evaluating how users with different literacies interact and understand interactive visualizations is a significant consideration to understand the impact of data literacy and the more suitable approaches to create visualizations that offer more insights (Boy et al., 2015; Borne et al., 2015; Rodrigues et al., 2020; Lee et al., 2020; Chevalier et al., 2018; DATALIT, n.d).

Considering the importance previously stated of using open data and thinking on how to engage citizens with different levels of visualization literacy, this study aims to answer the question: How can organizations, supported by open data and data visualization techniques, build visualizations that communicate information effectively to groups with different visualization literacy levels?

1.2. STUDY RELEVANCE

The importance of this study depends primarily on the understanding that data is becoming more available to the overall public and a need for modern life. As there is a knowledge gap that makes it difficult to develop accessible data visualizations for the general public, it is important to understand how technical and non-technical users understand visualizations (Blascheck et al., 2019). Studies were developed to evaluate how different groups of individuals react to visualizations and discover interactivity, however, most of them do not consider the visualization literacy level of users and how differently they feel about each visualization. Moreover, the existing work regarding ways of improving open data from governmental portals is usually focused on experienced users, normally from open data intermediaries. There is scarce research on how the everyday citizen can take advantage of such data, considering the restricted understandability of raw data (Chua et al., 2020). This study can be helpful as it indicates the existence of a gap between users with different literacies levels regarding the information acquired, thus impacting insight generation and decision-making. Therefore, the results obtained from this work can serve as foundation to the development of initiatives to improve data and visualization literacy skills and empower citizens (Gebre & Morales, 2020).

The results of this study can also support the improvement of existing or in development visualizations for other open datasets, avoiding non-effective visualizations for technical and non-technical groups, while increasing understanding and user autonomy. More than that, this study can contribute to the literature, as there is a lack of research on designs for open data (Lee, 2020). Also, this study can serve as a starting point for organizations that work with data journalism and aim to make an impact on data because data visualization is a highly effective technique to tell compelling and complex stories while guarantees journalism accountability (Alexandre, 2016).

Additionally, by analyzing TWB project database, it will be possible to understand how the international scenery impacts the sponsored initiatives and how TWB acts to accommodate new necessities and reallocates resources. Educating citizens concerning the existence of such databases is also important because it enhances the institution's transparency, especially concerning audit matters and on how the investments are being distributed, and if the institution's mission is being accomplished. To include the community, it is mandatory to comprehend how they interpret and understand data from platforms such as the one from TWB.

The reasonings above show why this study is relevant to be conducted since data visualization and interactivity proofed to be significant tools to enable clear communication and effective data analysis. Evaluating the best visualization and interactivity techniques for groups with different visualization literacy levels is essential both for private and public matters, especially targeting the general audience. This study offers an overview of how public and private agencies can use visualizations and interactivity to educate and communicate to different audience groups and which techniques are perceived as more effective for each group.

1.3. STUDY OBJECTIVES

Taking into consideration the context showcased in the previous session, the main purpose of this project is to create a prototype using the software Microsoft Power BI and data from The World Bank Data Catalog to create interactive visualizations to effectively communicate specific information about TWB lending projects to both the general public and data technical users, specifically aiming to understand how data visualization principles and interaction techniques can offer more effective responses for groups with different visualization literacy levels.

Next, the other main goal of this study is to evaluate the effectiveness of the prototype and validate the results.

1. Evaluate the most effective visualization and interaction techniques for each group of individuals in improving visual analysis and communication.
 - 1.1 Assess data visualization and interaction literature.
 - 1.2 Develop a prototype with different interactive visualizations to process The World Bank's lending projects open database.

2. Compare the effectiveness of the visualizations created and assess if there is a difference in how each group discovers interactivity.

- 2.1 Define a methodology to validate the user experience.

1.4. THESIS STRUCTURE

The thesis is structured into 6 chapters.

The first chapter is the introduction, where the thesis' background is explored along with the study's objectives and relevance.

The second chapter is related to the literature review. This includes an overview of existing work related to the thesis and relevant information to justify and offer foundations to the presented work. There is a discussion regarding the concept of open data and data, information, visualization, and digital literacy, and the context of DATALIT project. Also, this chapter is contemplated with a background in data visualization concepts, storytelling, and interactivity. Finally, there is a summarize of previous works about visualization effectiveness and how to measure it is explored.

Next, in the third chapter, the methodology is described in detail, with the reasoning for choices regarding the study's framework, tools, dataset, and assessment approaches. The methodology framework is the Design Science Research Model. Also in the third chapter, the storyboard, and the derived conceptual model for the development of the prototype are presented along with design considerations. Finally, a description of the prototype development and includes the rationalization for the visualizations' choices and validation, including explanations and interactivity of each view, among technical details.

In the fourth chapter, the prototype and the experiment results are described, followed by a chapter with a discussion of results. Finally, the last chapter includes conclusions from the study, limitations, and recommendations for future research.

The appendix includes the questionnaire developed for the experimental phase.

2. LITERATURE REVIEW

2.1. OPEN DATA AND THE WORLD BANK

Studies have indicated data as a conceivable tool to deal with social issues, ranging from federal to community and neighborhood level. The use of data can transform the lives of each citizen individually through its use in community economic development, urban and disaster planning, and decision-making in citizen's everyday life (Yoon et al., 2018; Kassen, 2013; Levin & Schneir, 2015).

Since the early 2000s, with the strengthening of internet and web technologies, governments and public institutions from many countries have made available publicly information about their services on the web. (Chua et al., 2020; Craveiro et al., 2016). Open data resources can be used as tools to enhance civic engagement, increase institutions' transparency, improve engagement between data consumers (usually citizens) and data publishers, create new products and solutions, policymaking, foster innovation, increase public awareness, and improve decision making for both public institutions and citizens. Moreover, with proper context and orientation, open data can be used to empower people to make better decisions to address community issues and improve everyday life (Jetzek et al., 2014; Chua et al., 2020, Gebre & Morales, 2020; Lee, 2020; Yoon et al., 2018). Yoon et al. (2018) interviewed data intermediaries' organizations that use data to enhance community decision-making based on data. They listed the reasons given by the companies for the importance of open data, such as developing community-specific programs or services, set new community goals, and apply for grants and funding.

In this sense, open data can be described as information that can be freely used, modified, and shared by anyone for any purpose or as open public sector information that is created, collected, organized, preserved, and made available freely for public use through government and public sector institutions (Gebre & Morales, 2020; Carrara et al., 2016).

The World Bank is one of the world's largest development institutions and was founded in 1944 to aid the reconstruction of countries after the World War II. Nowadays, TWB Group is composed of 5 different institutions that offer loans, knowledge, and advice to more than 100 developing countries. The main sectors TWB supports are climate change, pandemics, and forced migration. (The World Bank, n.d.). Plenty of data regarding TWB projects and studies are offered in an open data catalog with several public databases. There are currently more than 19.000 datasets offering time series, microdata, and geospatial data. Most of TWB datasets are updated frequently and provide reliable information on the socioeconomic status of many countries and TWB projects. The information offered by TWB is directly related to its mission and goals, that is to end extreme poverty worldwide and support countries' sustainable economic growth and shared prosperity.

2.2. LITERACY

2.2.1. Data Literacy

The literature in data literacy has been increasing in the last years and relates the subject with science education, technology, media, and civic education. There are studies relating data literacy skills and economic or social status, health, disabilities, race, cultural position, and gender (Carmi et al., 2020; Raffaghelli, 2020; Pedersen & Caviglia, 2019; Pothier & Condon, 2019). Studies concluded that data literacy skills are not only important to data scientists and analysts, but it also has a significant role for employability in modern work needs and active citizenship, where it is common to work with data for different purposes. Data literacy can be seen as a concept with the purpose to promote social justice and public good, balance power relations and asymmetries, reduce social, economic, and political inequalities and raise awareness against dis-/mis-/mal-information, since it allows people to understand, challenge, question, and protest. More than that, the capability to read and verify news and content, allows the user to understand the economics behind media and digital platforms, data privacy, and individual and collective rights, confirming that data literacy has a political, civic, and ideological aspect. (Carmi et al., 2020; Špiranec et al., as cited in Carmi et al., 2020)

In this context, the importance of data literacy is also a social issue. There is evidence that the general audience still did not reach all data-related capabilities because of the low levels of data literacy. When users present a certain level of data literacy, they can engage with different sources of data or produce their data and interact with it. This is relevant especially when we consider that many public policies and media reports are created relying on data and that our daily life is composed of many data-driven technologies, as sharing economy apps and smart meters. Therefore, data literacy is the capacity to critically assess, comprehend, and use data promotes citizen empowerment, data inclusion, and equips citizens to understand the principles and challenges of data. Consequently, people understand and interpret everyday data to manage data-driven decisions and argument, and foster citizen innovation (Wolff et al., 2019; Bhargava et al, 2015; Cobb and McClain, as cited in Wolff et al., 2019; Bhargava et al, 2015; Janssen et al., as cited in Wolff et al., 2019).

Bonilowska et al. (2019) describe a data-literate individual as the person that can understand information extracted from data and summarized into simple statistics. The individual can make calculations based on the statistics and use them in decisions making. A suggested framework for data literacy was described by Mandinach & Gummer (2016). The authors evaluated the state of art in this subject and identify 5 components: (1) identify problems and frame questions, (2) use data, (3) transform data into information, (4) transform information into a decision, and (5) evaluate outcomes.

2.2.2. Information Literacy

There are authors (Schield, 2004; Bhargava et al., 2015; Calzada Prado & Marzal, 2013) that define data literacy as a central component of information literacy. Most frameworks and competencies that aim to

described data literacy are aligned with the Association of College and Research Libraries' Information Literacy Competency Standards for Higher Education (Pothier & Condon, 2019). The proposed definition of information literacy is related to a set of abilities to recognize when information is needed and being able to locate, evaluate e effectively use it. The Association also describes six tasks an information literate individual must be able to tackle: (1) determine the extent of information needed, (2) access the needed information effectively and efficiently, (3) evaluate information and its sources critically, (4) incorporate selected information into one's knowledge base, (5) use information effectively to accomplish a specific purpose, and (6) understand the economic, legal, and social issues surrounding the use of inf (Association of College and Research Libraries, 2000).

Paor & Heravi (2020) address two information literacy frameworks. The CILIP's model is a one-size-fits-all approach with generalized basic skills to information literacy. They are: (1) A need for information, (2) the resources available, (3) how to find information, (4) need to evaluate results, (5) how to work with or exploit results, (6) ethics and responsibility of use, (7) how to communicate or share your finding, and (8) how to manage your findings. The second framework was developed by the Society of College National and University Libraries. The Society created the Seven Pillars Model. The pillars correspond to cycles and the competencies can be developed independently. The primary competencies are: (1) Identity, (2) Scope, (3) Plan, (4) Gather, (5) Evaluate, (6) Manage, and (7) Present (Paor & Heravi, 2020).

Nowadays, society faces challenges because of the multiple available types of media, quality uncertainty, and the expanding quantity of information. This can create doubts on authenticity, validity, and reliability due to the difficulty for people to evaluate and understand all collected information (Association of College and Research Libraries, 2000). In the same way as data literacy, information literacy is also imperative to enable citizens to actively participate in their community affairs and involve more It can also be a tool to combat fake news and allows an individual informed opinion of a local, national and international scale. Information literacy skills can be influenced by political, economic, and socio-cultural factors. After this reasoning, information literacy can be understood as an empowering competence that permits citizens to contribute and engage with society (Batool & Webber, 2019; Paor & Heravi, 2020).

Lee et al. (2020) also share a similar point of view by stating that there are cognitive barriers as different levels of information literacy and the perceived information overload that can lead to resistance in citizen's use of data and a diverse understanding and impact of open data in user's everyday life. The authors explain that information literacy is also important to receive and process information and develop responses; when the user exceeds his capacities, it is harder to identify relevant information and understand relationships or connections. In the study, the authors evaluate how personal factors such as information literacy affects perceived information overload, usefulness, and trust in government open data websites. The conclusion was that the higher the information literacy, the lower the information overload is perceived. Besides, the lower the information overload a person perceives, the higher usefulness the user realizes, which positively affects one's trust in a website.

2.2.3. Visualization Literacy

Visualization literacy is defined as the capacity to use data visualization to translate questions into visual queries, interpreting visual patterns, and extract or manipulate information from graphical representations. In other words, visualization literacy is the ability to use well-established data visualizations to deliver information in an effective, efficient, and confident manner, or the ability to make meaning, interpret patterns and correlations in visual representations of data (Boy et al., 2015; Börner et al., 2016).

Rodrigues et al. (2020) and Lee et al. (2020) affirm that visualization literacy research assesses many types of literacy, including data literacy. This is also argued by Chevalier et al. (2018), where the authors state that the concept of visualization literacy should be considered along with other literacies and abilities, as data and information literacy, because it is important to the user to be able to analyze different information sources, inquire about data collection, critique data, and question the credibility of sources. Chevalier et al. (2018) go even further and affirm that the concept of visualization literacy should be expanded to include all principles and skills for creating visualizations, not only to interpreting data, considering the ability to understand when and how to create visual representations to extract information. Critical thinking is also an essential component to the authors, as visualizations can be misleading and propagate perceptual and cognitive bias.

The assessment of visualization literacy is useful for understanding the target audience's capacity of reading visualizations, evaluate the acquired knowledge of students, hiring capable analysts, and defining a standard for visualization literacy (Boy et al., 2015). A study conducted by Blascheck et al. (2019) concluded that low levels of visualization literacy can influence the user preferred type of visualization. In the experiments made by Boy et al. (2016), visualization literacy levels demonstrated to reflect on how the user discovers and engages with interactive visualizations. The authors concluded that low literacy levels users may have a minor propensity to interact and discover visualizations and do not have strategies to find the required answers with the aid of visualizations. Also, the authors explain that if a user lacks visualization literacy, the cost of interacting with the representation can be perceived as higher than the benefit, as the latter is unknown. However, the literacy problem seems to be solved when questions and charts are highly congruent.

In this context and considering that nowadays visual representations are very present in everyday life and many institutions deliver information and stories through the use of them, visualization literacy is essential for citizen's empowerment, as it is a decisive tool to combat misinformation, enhance learning and create a more informed society. (Chevalier et al., 2018; Lee et al., 2020).

2.2.4. Digital Literacy and Competence

Jin et al. (2020) introduce digital literacy as a multidimensional framework and an essential capacity to conclude daily tasks in the 21st century. The authors also point out that in literature, the concept of

digital literacy is also referred to as computer and/or information literacy, however, the concept can be referred to as uses of all kinds of digital devices and environments.

Digital literacy can be defined as the required skills to achieve digital competence, or the ability to assess and communicate information through digital technologies. In this context, digital literacy includes competencies as information literacy and data literacy (Jin et al., 2020; Law et al., as cited in Jin et al., 2020). A digitally competent individual is a person able to use digital technologies in a critical, collaborative, and creative way, and knows information storage, data protection, content creation, and netiquette. With this set of skills, an individual can prosper in all areas of a digital economy and society (European Union, 2016).

The Digital Competence Framework for Citizens (DigComp) is a framework for digital literacy developed by the European Commission that aims to be a common reference for measuring competencies and identify gaps in knowledge, skills, or attitudes. The DigComp framework can be used for self-assessment, skill-job matching, support public policies that support digital competencies development, and appropriate development of training and education packages (European Union, 2016). Regarding the proficiency levels, the eight levels are based on the complexity of tasks the user can handle, their autonomy, and their cognitive domain.

The DigComp framework (EU Science Hub, n.d.) describes 21 competencies in 5 key areas with 8 proficiency levels:

- **Information and data literacy:** locate, retrieve, critically assess, organize, and judge the relevance of data, information, and content.
- **Communication and collaboration:** interact, communicate, and collaborate in public and private digital services, manage its own digital identity and be aware of diversity.
- **Digital content creation:** create and edit content, copywriting and licensing understanding, the capacity to give instructions for a computer system.
- **Safety:** protect devices, content, personal data, and privacy, and be aware of the environmental and social impact of digital technologies.
- **Problem-solving:** identify problems and needs, the capacity to use digital tools to innovate and be aware of digital evolution.

2.2.5. DATALIT Project

The DATALIT project is a joint research project coordinated by the Italian National Research Council and founded as a Knowledge Alliance under the Erasmus+ Program by the European Commission (Project reference: 612561-EPP-1-2019-1-IT-EPPKA2-KA). The consortium is composed by 14 partners, from

universities to business, from countries as Italy, Portugal, Albania, and Germany. The main goal of the project is to promote data literacy both in higher education and business levels (DATALIT, n.d.).

The project has assessed challenges to understand learning needs, competences, and quality levels to create a standardized definition to data literacy and the competences behind it. With a common syllabus it will be possible to develop competence-based courses to develop and fining tune students and employee's data literacy. To complete this challenge DATALIT partners use a LEVEL5 validation system to identify learning outcomes and indicators for each competence, thus collaborating to a Europe-wide system and stablish a reliable data competence reference system (DATALIT, n.d.).

DATALIT defines clusters of key specific competences related to data literacy:

- **Domain Specific (“Data”) Competences:** Digital (Critical Thinking) Literacy, Data Processing Literacy, Data Management Literacy
- **Social Competences:** Teamwork, Intercultural Communication, Leadership, Client Orientation
- **Organizational Competences:** Project Management, Planning and Resource Management, Networking, Evaluating/Reflecting, Client Orientation
- **Personal Competences:** Creativity, Problem Solving, Critical (Ethical and sustainable) thinking, Flexibility
- **Competences related to mentoring and coaching**

2.2.6. Conclusion

Considering the previous sections where data literacy, information literacy, visualization literacy, and digital literacy are presented and discussed, this project will divide the different groups of users to be evaluated according to their data visualization literacy levels.

This concept was chosen because the main goal of this project is to evaluate how users interact with visual representations presented to them by the author, without the need to assess or manage sources or data collection and processing approaches. The users will be evaluated by their capacity to find answers, engage, and understand the information delivered by the visualizations.

Besides, as reviewed in the latest sections, according to the DATALIT project and the literature, visualization literacy is a concept that encompasses principles of data, information and digital, thus contributing to the choice to evaluate visualization literacy, as it is possible to have a more comprehensive approach.

2.3. DATA VISUALIZATION

Data visualization is the use of visual elements and graphical representation of information and data. The accurate use of data visualization techniques is indispensable in a world where information can be abstract and the amount of data immensurable. These techniques work as an intermediary step to convert data into information by amplifying cognition and helping make sense of data, discover trends and outliers, that would not be accessible to the bare eye (Alexandre, 2016; Concannon et al., 2018; Tableau, n.d.). Visualizations are composed of marks and channels. Marks are the elements that represent items or links. Channels are related to marks' appearance and encode information in terms of magnitude (how much) or identity (what or where) (Munzner, 2015).

Still, based on Munzner's work, the author lists 8 rules of thumb for data visualization, that were applied in this project:

- No unjustified 3D
- No unjustified 2D
- Eyes beat memory
- Resolution over immersion
- Overview first, Zoom and Filter, Details on demand
- Responsiveness is required
- Get it right in black and white
- Functions first, form next

Besides those rules, an interesting practice to enhance the insight gain and engage the audience is to include principles of storytelling and narrative visualization (Alexandre, 2016; Dove & Jones, 2012).

2.3.1. Narrative visualization and Storytelling

Earlier, data visualization was based on static visualizations, with diagrams and charts, combined with a great amount of text. The text would tell the story while the pictures offered evidence and details. In this setup, stories were told in a controlled progression, as in movies. More recently, stories are still expressed in a linear sequence, but they also include an interactivity component that invites the users to verify and question assumptions (Segel & Heer, 2010).

Narrative visualization is described by Dove & Jones (2012) as the combination of interactive exploratory techniques and communication through the narrative to generate new opportunities to promote insights. Segel & Heer (2010) have a similar approach, describing narrative visualization as the

combination of storytelling techniques and interactive data visualization. In this context, storytelling can be understood as the action to bring stories visually and contextually to life relying on data and turning this story into actionable insights by impacting the audience (Knaflic, 2015).

There are 2 main approaches to how stories can be told in visualizations: author-driven and reader-driven. Usually, visualizations have an approach between the two extremes (Segel & Heer, 2010). Table 2.1 briefly describes both approaches.

Table 2.1 - Properties of Author-Driven and Reader-Driven Stories (adapted from Segel & Heer, 2010)

Author-Driven	Reader-Driven
Linear ordering of scenes	No prescribed order
Heavy messaging	No messaging
No interactivity	Free interactivity

Segel & Heer (2010) describe 3 schemas that follow a combination of these approaches:

- **Martini Glass Structure:** begins with an author-driven approach with questions or written articles to present the content. It is also possible to not use texts but only a default view and annotations. After the author’s narrative is done, the reader can freely interact with the visualization.
- **Interactive Slideshow:** the structure is similar to a slideshow with the addition of an interactive mid-narrative in each slide. The mid-narrative is the balanced use of the author and reader-driven approaches as it first passes the author’s view and then allows users to explore the visualization by themselves before passing to the next view.
- **Drill-Down Story:** this schema starts with an overview of the visualization subject and the user can choose what part they want to further explore and learn the story. The user decides which stories will be told and when, however, the author still must define the interactions, the stories, and the details included.

2.3.2. Interactivity

Open data often are composed of massive datasets with technical information, little or no metadata, and available as raw tabular files. This setup is not easy to be read and understood, especially by non-technical users. To make this data accessible to the general population a solution is to create interactive visualizations as interactivity is as a fundamental instrument to aid visual exploration and insight generation with less expertise (Blacksheek et al., 2018; Boy et al., 2016). In this context, interactive data visualization enables the user to experience the same insight discovery path from the visualization’s author. The user is guided by a narrative context in which the cognitive load is minor than in the unguided discovery. Besides, interactivity allows the user to have different displays and alter the views,

accepting support queries that need more than one visual encoding (Dove & Jones, 2012; Munzner, 2015). Interactivity is also an interesting solution to issues as over-labeling, visual clutter, excess of color or hue, and information hiding. The interaction also allows for unexpected discovery and active data analysis manipulation to gain insights (Ruchikachorn & Mueller, 2015).

Figueiras' (2015) summarized 11 interaction techniques to use on data visualizations. The techniques are listed on Table 2.2 – Interaction techniques (adapted from Figueiras, 2015).

Table 2.2 – Interaction techniques (adapted from Figueiras, 2015)

Interaction Techniques	Description
Filtering Selecting	Simplest technique to reduce the complexity of the visualization and quickly emphasize items of interest. Use of dynamic filters or queries. Allow immediate response.
Abstract/Elaborate	Allows the user to choose the amount of information displayed: Zooming or Details on demand techniques. It is essential that the transition between zoom levels is smooth to preserve the sense of position and context. Use of zoom, drill-down, tool-tips, or pop-ups. It can provide backstories and increase user's engagement and attention.
Overview	Explore tools allow examine different subsets of data from the overview.
Connect/Relate	Shows the relationship between items, for example, by highlighting items of interest
History	Entitle the user to retrace his actions and undoing mistakes while exploring the visualization. This tool is not very common in today's visualizations
Extraction	Allows the user to keep and share their discoveries, avoiding to repeat steps in exploration
Reconfigure	Means changing the spatial representation of data allowing perceiving new trends and perspectives. This can be achieved by rearranging columns, rows, or axis attributes or even by offering a new visualization
Encoding	Changes based on color, size, or shape.
Participation/ Collaboration	Allows users from different places to share their insights and data interpretations. Also, it is possible to create tools where the user can add new information and messages. The approach increases user's engagement as they can dialogue, challenge each other, and explain their points of view.
Gamification	Add game mechanics or game design patterns in the visualization.

Some studies evaluated the gain interactivity can bring to data analysis and comprehension. For example, a study conducted by Böschén et al. (2017) evaluated if the option to interactively aggregate bars as stacks in an aggregation of data tasks would result in faster, easier, more precise, and more satisfying activities. The authors were able to support their hypothesis, independent of the complexity of the bar chart. Abell & Churcher (2008) also studied the impact of interactivity on stacked bar charts and concluded that the use of interactivity features improves the effectiveness and the facility of data interpretation. However, interactive functions were not useful for spotting missing segments. Géryk (2015) defends animated visualizations as a tool to enhance data analysis and manipulation, helping the process of human pattern recognition and the perception of change values while enhancing learning and keeping the user's attention and engagement. The research compared static and animated visualizations

and concluded that animated techniques resulted in fewer errors for larger datasets, besides being more interesting and entertaining. Adnan et al. (2016) conducted a study about time series visualizations. The results from the work were that positional and color visual encodings were more effective than area visual encodings for maxima, minima, and trend detection tasks. Additionally, it optimizes user experience, without any loss of efficiency or accuracy.

However, it is not clear yet how the general audience or web users understand visualizations and discover interactivity in them. Even when text and visualizations can co-exist, it should not be assumed that everyday internet users will think it is obvious that they should use interactivity to explore data, and the number of interactivity techniques can limit the effectiveness of visualization or create a high cognitive load. Additionally, the task to create interactive visualizations is more challenging when tasks are open-ended in nature. On the other hand, users can be motivated to engage with interactivity if they are shown the possibility (Blacksheck et al., 2018; Boy et al., 2016; Baigelenov & Parsons, 2018).

Blacksheck et al. (2018) affirm that there is a knowledge gap in interaction discovery, especially for the general public, which makes it a challenge to develop accessible visualizations for this group. The authors investigate strategies 3 groups of users (novices, savvy, and experts) use when discovering interactivity in open data visualizations without any explanation of the views. The study employed eye-tracking technology to evaluate the areas in the visualization that users are drawn to and how their attention shifts during tasks, as well as interaction logs and audio and video recordings. In the same study, the authors concluded that individuals oscillate many times between interactivity controls and the visualizations to understand the effects of the interactivity on the views. Additionally, participants tend to focus more on the controls instead of the visualization itself, where you encounter most information to be communicated. This could be because the controls served as interactive legends and users wanted to verify selections and compare color encodings. An exception of this behavior was on the bubble chart, probably because this chart was interactive, with data being shown when the mouse passed over a bubble. Another interesting behavior detected in the study was that all users made a pause while interacting with any view. During this interval, individuals would scan the visuals. The authors compiled their discoveries into different approaches to create interactions that are more discoverable, that are described in Table 2.3.

Another relevant work regarding how interactivity is perceived is from Boy et al. (2016). This study suggested that users often do not notice the different interactive tools, especially if embedded with text, and as a solution, present the suggested interactivity (SI) as “a set of methods for indicating that a graphical area can be interacted with by subtly directing a user’s attention so as not to impede too heavily on this person’s focus or the rest of the interface design”. They exemplify with the use of motion and pictographic symbols, where the combination of both could help to explain the purpose of a tool and demonstrate its functionalities.

Table 2.3 – Approaches to more discoverable interactions (adapted from Blacksheck et al., 2018)

Approach	Description
Inviting interaction	This approach suggests hinting users using feedforwarding, revealing animations, or emphasizing that changes can happen.
Providing entry points	This approach engages people as the users can insert personal input to query data and interact with the visualization, such as browse for their home country.
Using spatial organization	Grouping sets of interactive controls taking advantage of a spatial organization (top-down, left-right, etc) so individuals can explore based on permutation and structural interactions.
Combating oscillation	Users spent much time oscillating between controls and charts. Also, the participants described this situation as “irritating”. This approach suggests integrating interactions into the data representation (spatial immediacy).
Supporting transition	Participants compare different views to assess what changed (visualization-to-visualization). This approach refers to create a smooth transition between views or datasets.
Scaffolding complex interactions	The study used an advanced interactive function that few people perceived. To avoid that, and allow users to have a better exploration experience, this approach suggests highlighting the functionality, for example, using stencil-based tutorials or scent cues.

The authors evaluated different visual cues to SI and performed 3 experiments using visualizations embedded with text. The first activity was regarding the use of charts to perform fact-checking; the second experiment was to evaluate if, given the chance to discover interactivity with SI to perform tasks, users would use them; and the last trial was to evaluate participants' propensity to interact with chart bias. The first experiment confirmed that most participants do not realize that the charts were interactive and did not use them, answering the questions with information from texts. The ones who discovered interactivity continued to use it in the next sections. In the second experiment, most users discovered interactivity and employed it to answer the questions. The authors considered that the minor use of charts in the first experiment was due to weak visualization literacy skills. Finally, the last experiment confirmed that there was no bias.

The final remarks of this work were the definition of three SI cues to apply in visualizations:

- SI cues in the object of interest, as the visualization itself
- SI cues in external objects, as widgets and buttons
- SI cues that are a mix of the previous cues and can provide feedforward.

Finally, it is important to draw attention to users' level of literacy, purpose, and experience. Those factors can impact how individuals interpret and interact with visualizations. For example, a novice individual could use the visualizations to learn while a domain expert would try to solve actual problems. Experts can also be aware of how to access additional information or controls to enhance exploration, while novices do not have this knowledge (Rouse et al., 2017).

In this context and regarding interactive visualizations to decision making, Oghbaie et al. (2016) believe that is not clear if the interactivity helps to support better decisions. If the visualization does not use the correct approaches, it can increase bias and identify misleading correlations, especially for novices. The

study defends that using the correct interactivity techniques allows to mitigate these effects and reduce the performance gap between experts and non-experts. The conclusion was that experts only exceeded the accuracy of non-experts when more complex causal relationships were involved. Also, both groups had the same speed and only experts made full use of all the information displayed.

As a final reflection for this section, users present different levels of visualization literacy and proficiency, as well as different preferences on how narratives are conducted and interaction techniques. It is possible to develop broad guidelines for more effective visualizations for the public, however, there is no simple answer to what the best interactive visualization approach is (Alexandre, 2016).

2.4. EVALUATION OF INTERACTIVE VISUALIZATIONS

2.4.1. Effective Visualization

Among the literature on data visualization, there are different concepts of “effective visualization”, and most of those definitions are often incomplete. Effectiveness can be related to several subjects involving concerns about support on tasks, correctness, accuracy, and truth. Also, the dataset, the defined tasks, and questions to be asked to assess effectiveness are only a few of the factors that impact the evaluation. User’s expertise, memory capacity, domain and tool knowledge and data literacy skills also influence effectiveness and users’ performance, although it is not well understood how. On the top of it, concepts as “faster” can be delicate as it is possible to consider the speed users move the mouse or visualization latency (Zhu, 2007; Zhu, 2017; Munzner, 2015).

Zhu (2007, 2017) studied the definitions of effectiveness for visualizations and his conclusions are highly regarded in the topic. Zhu separated 2 groups of concepts that explain effectiveness:

- **Data-centric view:** effectiveness depends on the correspondence between visualization and displayed data. In other words, it tries to measure if there is a match between the structure of data and visualization.
- **Task-centric view:** effectiveness depends on specific tasks. It means that visualizations should be designed to complete a particular task. This approach is most common in empirical psychology and computer-interaction studies.

Then, Zhu (2017) also explains that there are 2 methods to evaluate effectiveness:

- **Heuristic evaluation:** visualization experts evaluate visualizations based on rules and principles.
- **User studies:** measures of task completion time, error rate, user satisfaction, etc.

Finally, the author defines effectiveness in 3 principles and how they relate to the visualizations:

- **Accuracy:** relationship with data - the visualization structure should be coherent with the dataset structure.
- **Utility:** relationship with tasks – visualization helps users achieve the goal of specific tasks.
- **Efficiency:** relationship with user – visualization reduces the cognitive load for a specific task over non-visual representations, making it easier to understand the data.

Each principle can be assessed using qualitative and quantitative metrics to measure visualizations’ effectiveness, taking advantage of the User Studies method. Table 2.4 exhibits suggested measurements for each principle.

Table 2.4 - Quantitative and qualitative measures of effectiveness (adapted from Zhu, 2007)

Principle	Quantitative measurements	Qualitative Measurements
Accuracy	Number of interpretation errors	Interview Observation Expert-novice comparison
Utility	Number of achieved benchmark goals Number of times a visualization design is selected by users to conduct a task	Interview Observation Expert-novice comparison
Efficiency	Task completion time Eye movement Learning curve measurement	Visualization complexity analysis Interview Observation Expert-novice comparison

The measurements enlisted in the table are applied in assessments for different works in the literature. For example, Böschen et al.’s (2017) experiment used 5 tasks with simple bar charts and 5 tasks with complex bars. Before starting the tests, users had the chance to complete a training task. All questions required a numerical value as answers and filled a questionnaire to collect feedback regarding their perception of the experiment on a 5-Point-Likert scale. Effectiveness was measured by calculating the deviation of the answers as a standard percentage. Also, the study computed task completion time and eye-tracking information.

Abell & Churcher (2008) evaluated 10 charts with interactivity stacked bar charts and recorded whether the answer selection was right, wrong, or “I am not sure”, total time, number of times the interactivity was used, number of clicks to the display segment and total values.

Adnan et al. (2016) initiate their experiment in time series visualization by explaining the purpose and procedure of the study to the users. After completing the training for the first task, participants completed 24 tasks in which they had to select an answer using drop-down menus of week and month. After the task, the participant answered two 5-point Likert scale questions about the confidence in the answer and the use of the visualization for the tasks. Users were advised to finish the tasks as quickly as possible and completion time was another validation measure.

Géryk (2015) asked the participants to complete 16 tasks, each with 1 to 5 required answers. Each task had students' IDs as the answer. The users had the opportunity to execute practice trials and were asked to complete tasks as quickly and accurately as possible. The study results were divided into three sections: accuracy, completion time, and subjective preferences and significant effects were measured with ANOVA. Accuracy was calculated as a percentage of the correct answers and user's preferences were assessed with surveys where individuals evaluated their preferences regarding analyses. Similarly, Concannon et al. (2018) evaluated the effectiveness of dashboards by measuring task completion time and answer accuracy. Participants completed a questionnaire regarding their knowledge on the subject domain, thoughts on the visuals and computer literacy based on a Likert scale. ANOVA testing was used for significance measurement.

As seen in the examples mentioned above, the use of the User Studies methods, as described by Zhu, is widely employed. The use of surveys and interviews to evaluate qualitative and quantitative measures is a common practice. The surveys may include open or multiple-choice questions when evaluating quantitative measurements, while the use of methods as the Likert scale and interviews are used to evaluate the user's feelings, engagement, and opinions about the visualizations.

This project will use a task-centric view, relying on the 3 principles exposed previously to define effectiveness and using user studies as evaluation.

2.5. CONCLUSION

The Literature Review conducted in this chapter related the concepts of data, information, visualization, and digital literacy and how those data-based ideas are essential for society development as whole, from an individual to an enterprise level. Assessing data literacy challenges and competences is important to understand users' data literacy levels and how to create data literacy competence-based learning modules, as the DATALIT project has been currently doing.

Reliable sources of data are usually offered by governmental and public institutions, called open data. However, most of time, open data are available in raw formats that are difficult for the public to understand it and create knowledge from it. The use of interactive data visualizations is an approach that can enhance information attaining, thus comprehending how the general and specialized audience engages with this method is important to develop more accessible and suited visualizations, especially considering that users' data literacy and experience can impact in the insight's discovery and interaction process.

Finally, there are studies and guidelines detailing techniques to enhance users understanding and engagement with interactive visualizations, plus, it is important to have a structured definition and methodology to evaluate the effectiveness of the developed visualizations.

3. METHODOLOGY

This section describes in detail the framework chosen to develop the work, including the justification of tools, data, prototype creation, evaluation, and validation of results. The methodology for this project is based on the Design Science Research Methodology framework, as suggested by Oates (2015). This process is composed of 5 stages, as shown in Figure 3.1. Each step will be detailed in the sections below.

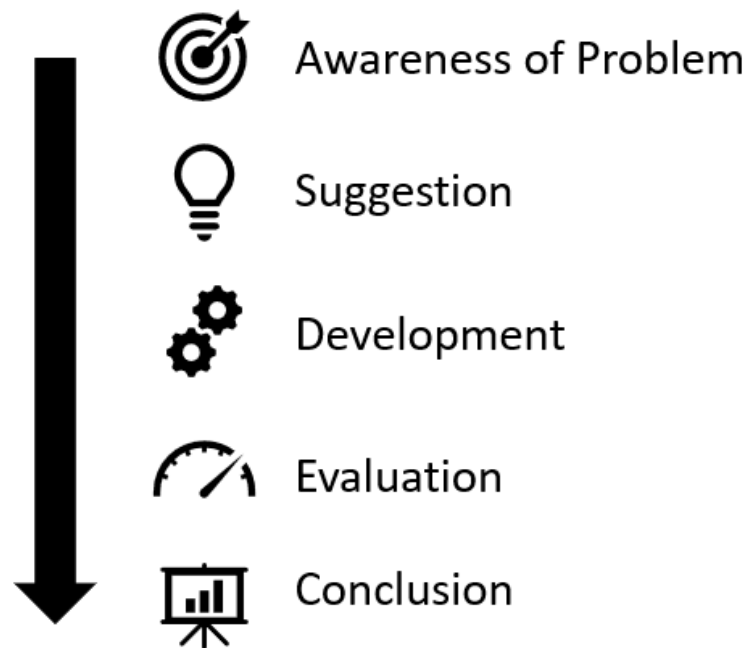


Figure 3.1 - Design Science Research Process Model

3.1. DESIGN SCIENCE RESEARCH PROCESS MODEL

Awareness of Problem

The awareness of the problem was the first phase of the project. In this stage, the problem was identified and characterized and the motivation for the project was enlisted. The rationale behind the project was conducted in the first chapter. In the introduction, the background for this study was detailed as well as its objectives and relevance. The literature review, in the second chapter, offers more detail to this stage, adding previous works in the field, concepts, and existing solutions to help to accomplish the project's goals.

For this project, the delimited problem is to evaluate how organizations, supported by open data and data visualization techniques, can build visualizations that communicate information effectively to groups with different data literacy levels.

Suggestion

The suggestion stage is where a new functionality or tool is envisioned based on a novel configuration of either existing or new and existing elements.

In this study, the suggestion was defined with the development of a storyboard and a conceptual model to be further developed into the actual prototype with different data visualization and interactivity techniques.

Development

This stage refers to the actual development of the prototype. To achieve all prototype goals, the guidelines described in the Suggestion phase were followed. Also, it is important to highlight that the development followed all data visualization rules of thumb and best practices, including accessibility matters. After the prototype was approved, the work proceeded with the next step.

Evaluation

After finishing the development of the prototype, the evaluation of all visualizations was conducted, aiming to validate the efficiency of each one. The evaluation was based on the literature review conducted previously and followed a task-centric view, relying on the principles of accuracy, efficiency and utility to define effectiveness and using user studies as evaluation.

The evaluation was conducted with surveys that included both quantitative and qualitative assessments. Some of the users were available for a quick interview after concluding the survey. Due to COVID-19 confinement limitations, the surveys and interviews were conducted online. The survey requested information about the user, regarding its background with data visualization and analysis, to define to which, group the user will be placed – high or low level of visualization literacy.

Finally, statistical analysis with the results were conducted to evaluate the difference between groups.

Conclusion

Finally, the last stage was the conclusion. The feedback collected from the evaluation phase was listed as improvements to be applied to the prototype, and considerations of how each group interacted and felt about each visualization were presented, along with differences between groups.

3.2. DATA

The public dataset for this project is provided by The World Bank via its Data Catalog website. The dataset concerns TWB Projects & Operations regarding lending for different countries and projects worldwide. This dataset was released in 2010 and is constantly updated. The version used in this project was collected on the website in January 2021. The selected period of analysis was between 1947 and 2020, included.

There is no interactive visualization available regarding the data on TWB website, thus this being another motivation to choose this dataset. Understand the chronological evolution and statistics of lending and projects' themes, along with the current international scenery, is important to understand TWB work and how it is compatible with its missions.

The dataset includes information about all WB's projects and their status (open, closed, pipeline, or dropped). Also, there are details on the project name, project sectors and themes, date of approval (if approved) and closing (if finished), monetary lending values by project and by institution, and geographical references. Details of data preprocessing are described next.

The dataset is available in CSV format at <https://datacatalog.worldbank.org/dataset/world-bank-projects-operations>.

3.3. TOOLS

The software chosen to create the prototype was Microsoft Power BI. Microsoft Power BI was launched in 2015 as a group of tools, connectors, and services that allow data visualization and analysis. This ready-to-use tool is compatible with a diverse range of data formats, including from cloud servers. The tool can assess a great amount of data and prepare interactive visualizations with agility and promptitude. Power BI is largely used as a report creation tool and allows the user to share their work online on the dedicated application page. It also provides a single user-friendly interface where it is possible to deal with data cleansing and preparation, filtering and creating the visualizations. Besides, there is a free version with a library containing many features (Lousa et al., 2019; Viorel and Lucia, 2019).

This tool was selected for many reasons. First, because there is a free version of the software with many features available and it is possible to share the developed content. Also, because the author has familiarity with the tool and aims to deepen her knowledge in the software, as nowadays it is widely used for data analysis and visualization in companies from different branches. Then, it is a ready-to-use solution that does not require programming skills, therefore allowing the final solution to be more easily implemented for a wider range of entities.

3.4. EVALUATION ASSESSMENT

Users were asked to complete an online survey concerning their background in data visualization and analysis and their experience with the prototype. The survey was divided into 3 parts: user profile, prototype's qualitative evaluation, and prototype's quantitative evaluation. It can be found in Appendix A.

The questions were created based on the concepts of effectiveness defined by Zhu (2007). For the accuracy assessment, it was evaluated the number of wrong answered questions. The efficiency assessment was based on the user task completion time, and 2 multiple choice questions where the user could evaluate how they felt regarding perceived information. Utility assessment was made through a user assessment of usefulness using a Likert scale. In addition, an alternative from Zhu's visualization complexity analysis was made using a qualitative assessment of complexity and engagement. Finally, users were questioned about the effectiveness, to compare this result with the concepts described before.

Some limitations of this assessment were due to the nature of the qualitative evaluation, which is highly subjective and can be influenced by the user's experience, domain knowledge, and visual-spatial capability (Zhu, 2007). In addition, the impossibility to have a controlled environment or in-person experiments due to COVID-19 confinement may have impacted the user's performance and results. Another limitation was that the participants had to change tabs between the visualization and the survey when answering the questions. This can lead to a higher response time and required the user to memorize the questions or going back and forth to remember them.

The final analysis was made by evaluating the qualitative and quantitative results of all questions and the interview with available users. To test for statically significant differences between both groups, an ANOVA single factor test was conducted based on the mean values of each measure, either qualitative or from the Likert scale questions. This approach was applied by authors as Géryk (2015); Concannon et al. (2018); Oghbaie, Pennock & Rouse (2016); Rouse, Pennonck, Oghbaie & Liu (2017); and Kwon (2016).

There is debate whether to use a parametric test as ANOVA to test Likert scale questions since the answers can be considered as categorical values and if we consider them as continuous variables it is complicated to assess equally the gaps between each item on the scale. However, there are papers defending the use of this technique with Likert data as long as the sample sizes are small, variances are unequal and there are non-normal distributions. Those works also affirm that it is appropriate to analyze Likert items based on sums, means, and standard deviations, therefore, allowing the use of parametric approaches (Carifio & Perla, 2008; Norman, 2010).

3.4.1. User Profile

The first part of the survey was regarding the subject's profile, aiming to evaluate the user's visualization literacy level and experience with data analysis and visualization. This questionnaire was answered by

the user before the user starts to interact with the visualizations. The survey included open and multiple-choice questions. Among the multiple-choice questions, some of them were based on the typical five-level Likert scale.

The questions covered:

- User age (open question).
- User education level (multiple-choice question).
- User study background (open question).
- User current professional activity (open question).
- User previous experience with data analysis and visualization (multiple-choice question).
- User knowledge of different data visualization charts (multiple-choice question).
- User experience and confidence in using data visualizations in everyday tasks (multiple-choice question with Likert scale).
- User knowledge in more specific visualization questions, as the concept of outliers and correlation (multiple-choice question).

With the results from this part of the survey, all users were divided into different groups, based on their visualization literacy levels.

3.4.2. Prototype Evaluation

The prototype's evaluation was divided into 2 sections: qualitative and quantitative. The first visualization, as it is only the cover for the project with context and instructions was not evaluated by the experiment's participants.

Both sections aimed to evaluate the effectiveness of the prototype, taking into consideration the principles of accuracy, efficiency, and utility (Zhu, 2007) and other studies addressed in the Literature Review. Also, another goal of this part of the survey was to evaluate which visualizations and interaction choices in the prototype were the most effective and the differences between how the different groups of individuals interacted with the prototype.

In the qualitative assessment, participants were asked to follow a specific set of tasks and record their answers in the survey. With the results, it is expected to understand if users were able to use the prototype efficiently. In this section, the time that each user took to finish the task was recorded. The questions were all multiple-choice questions, and all questions could be answered correctly using the

visualizations. It was possible to tackle different approaches to correctly answer the questions. In some of the questions, the user could select the option “I don’t know / It is not possible to answer”.

In the qualitative assessment, the users were asked to classify the visualizations and interactive features individually in several aspects, as the level of utility, effectiveness, engagement, and complexity. The answers were provided in the Likert scale, and for the tools, there was the option to select “Not used”. Concerning the whole prototype, each participant was asked to evaluate its performance in the use of the prototype, considering the level of comprehension and insight generated, as well as the level of utility, effectiveness, engagement, and complexity.

At the end, users were also asked to rank each one of the visualizations that compose the prototype in order of preference and an open space was available for any improvement suggestion and commentaries.

3.5. STORYBOARDING AND CONCEPTUAL MODEL

According to the Design Science Research Model described in the Methodology, the Suggestion phase includes a conceptual model of the prototype. The conceptual model was created based on storyboarding techniques, with the main goals to plan the story to be told the audience, how it would be communicated and what would be the content of each visualization. The conceptual model also is vital to achieve a cohesive layout, where all visualizations and tools fit together, and information is displayed effectively.

The main story the prototype showcases is how TWB funding changes with the international scenario and how resources are reallocated, with attention to the COVID-19 situation at the end. This was achieved by analyzing patterns and trends of TWB investments, along with reports provided online by TWB. With the story defined, it was decided to develop 5 visualizations. The first visualization (V0), as it is only the cover for the project with context and instructions was not evaluated by the experiment’s participants. The storyboard sketch and visualizations’ justifications are on Figure 3.2 and Table 3.1.

Each visualization covers different themes, so the user does not need to go back and forth to understand the information. This strategy is used to avoid oscillations and the user’s annoyance (Blackscheck et al., 2019). There are also suggested actions for the user in the text, as a SI cue that use feedforward (Boy et al., 2016). Color blindness is also a concern to be considered. Plus, following the ideas of spatial organization and entry points by Blackscheck et al. (2018), the prototype has a designed space for a sidebar with interactive tools and a small text providing context to the page, following the suggestion to scaffolding complex interactions of the suggestions by Blascheck et al. (2019). To achieve a standardized design, the generic structure of the dashboards was represented on Figure 4.1 to Figure 4.4.

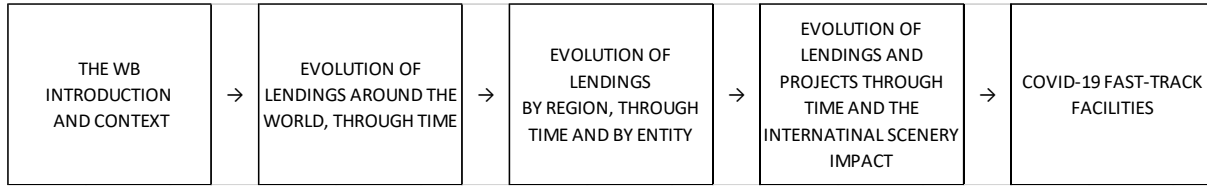


Figure 3.2 – Storyboarding sketch

Table 3.1 – Visualizations’ justification

Visualization	Justification
V0	Introduction and context
V1	The WB mission: to end poverty and build prosperity of developing countries - Map to evaluate where the lendings are going and if the allocation is faithful to The WB mission.
V2	Lending Entities IDA and IBDR: each entity has a priority in lending. The chart aims to evaluate what regions each institution prioritizes.
V3	The WB mission: charts aiming to evaluate the growth in the number of projects and lending, and the impact of the international scenery in the maintenance of The WB missions.
V4	COVID-19 fast track facility: Understand how the facility impacted projects' decisions.

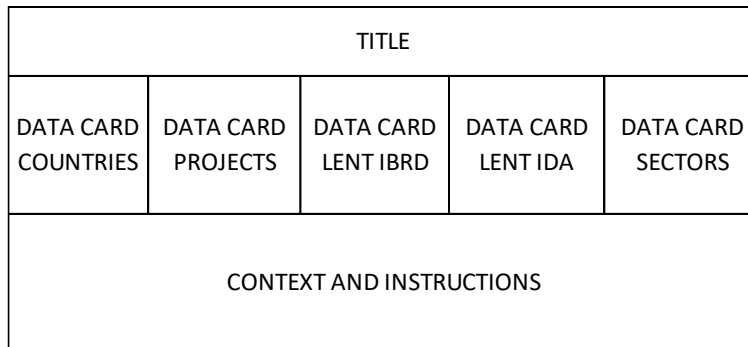


Figure 3.1 – Conceptual Model V0

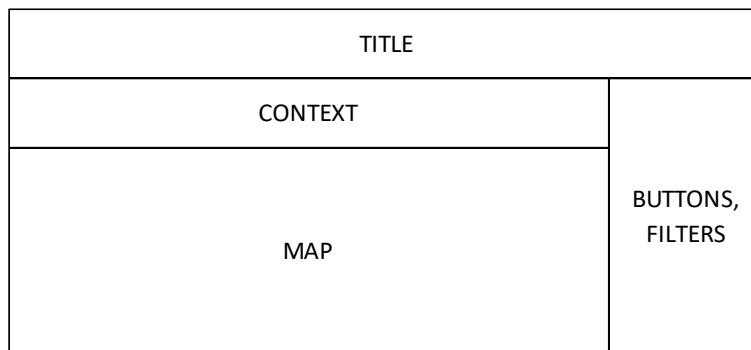


Figure 3.2 – Conceptual Model V1

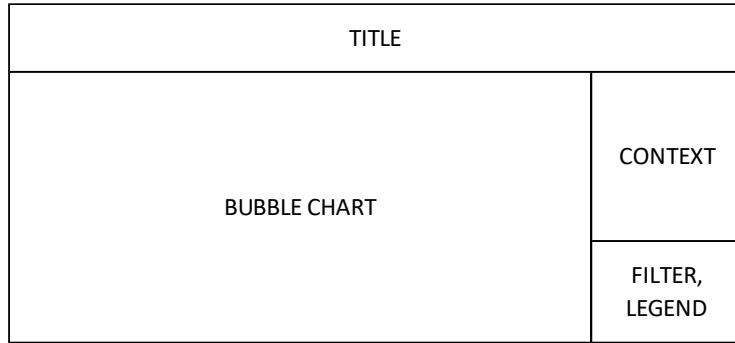


Figure 3.3 – Conceptual Model V2

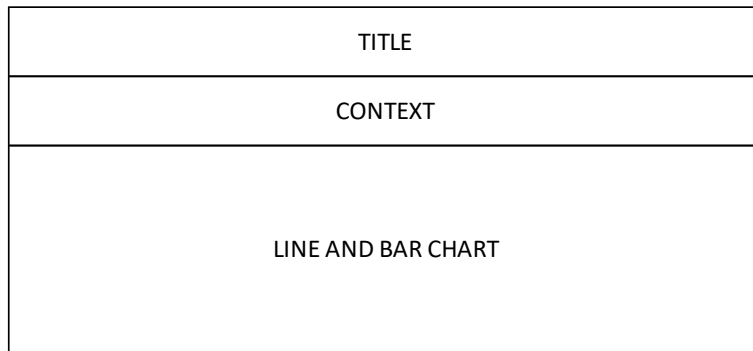


Figure 3.4 – Conceptual Model V3

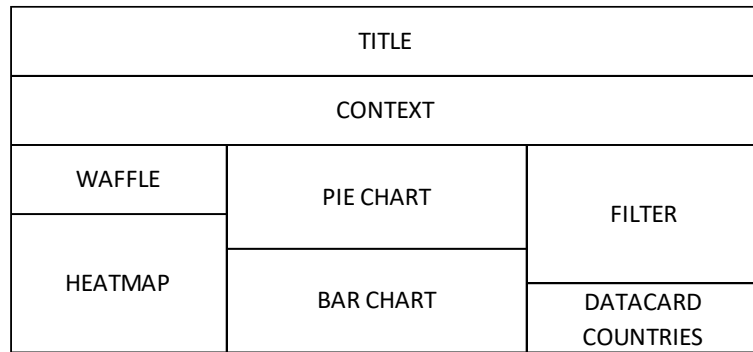


Figure 3.5 – Conceptual Model V4

3.6. PROTOTYPE DEVELOPMENT

3.6.1. Data Pre-processing

Data transformation, standardization, and cleaning processes were needed to achieve the desired visualizations. The tasks below were executed with the support of Power BI Power Query Editor:

Table 3.2 – Data pre-processing tasks

Data Pre-processing
Rename columns to better understanding.
Change of data types of columns with monetary values: from text to decimal.
Filter out projects approved in 2021.
Filter out projects with "Status" as "approved" and without "Approved date".
Filter out projects without "Status".
Create a new column "Month": based on the name of the month of the project's approval date.
Create a new column "Type": based on whether the project was directly related to COVID-19 or not.
Replace the value in the "Region" column: Other → World.
Replace the value in the "Project Major Sector" column: null → Other.
Replace the value in the "Project Major Sector" column: Health and other social services → Health.
Replace the value in the "Project Major Sector" column: Electric Power & Other Energy → Energy and Extractives.
Replace the value in the "Project Major Sector" column: Information and Communications Technologies → IT and Communication.
Remove columns "Program Type", "Supplement Project Flag", "Project Status Display" and "Project Sector".

3.6.2. Storytelling

The intention of telling a story while showing information increases user comprehension and is likely to increase engagement (Blackscheck et al., 2019). The storytelling was supported by the creation of a storyboard and based on the narrative visualization schemas enlisted by Segel & Heer (2010).

The chosen schema was the interactive slideshow. According to Segel & Heer (2010), this schema's structure presents mid-narratives in each slide and uses annotations or texts. This method balances the author and reader-driven approaches, allowing the author to showcase a view and the user to explore the visualizations freely. Based on this, the visualizations were developed with messages and a considerable level of interactivity, and the user was able to use the given information to support exploration.

Other resources were used to sustain storytelling and maintain the integrity of the narrative:

- **Color:** employed to reference, group, or highlight the desired information.
- **Texts, legends, tooltips, and pop-out features:** offer more context and further details to the user. It also sets the user's expectations for the view's content and an idea of how to start the analysis.
- **Filtering, selecting, zooming and overview:** allows to choose the amount of information displayed.
- **Animations:** facilitates the understanding of evolution in time and allows the user to evaluate how the showcased variables have changed.

- **Suggested interactivity:** use of cues in the visualization and external objects, and pictographic symbols to indicate the presence of interactivity.

3.6.3. Color Accessibility

Color blindness is an issue that should be addressed when constructing data visualizations. The chosen color schema can affect the analysis and comprehension of people who suffer from this deficiency.

The color palette was selected considering color blindness best practices and as there are different classes of color blindness, thus the use of color blindness simulators was applied for all existent classes and in all visualizations. This was achieved with the support of the following resources:

- **Color Space:** www.mycolor.space
- **Coloring for Colorblindness:** www.davidmathlogic.com/colorblind
- **Color Blindness Simulator:** www.color-blindness.com/coblis-color-blindness-simulator/
- **ColorBrewer:** www.colorbrewer2.org/

3.6.4. Content of Visualizations

This work’s goal is to understand how users engage and understand different visualizations and interactions, trying to define which one is preferred by users with different visualization literacy levels, thus the use of different types of visualizations was prioritized and the use of suggested interactivity was employed in some cases.

The first visualization, as it is only the cover for the project with context and instructions was not evaluated by the experiment’s participants.

In this chapter, each visualization is described considering the following items: Main Message, Visualization Type, Marks, Channels, Interactions, and Data Filtering and Tasks (Table 3.3 to Table 3.10).

Table 3.3 – Content of V0

Visualization	V0 - Introduction
Main Message	To offer context, references, and an introduction to the prototype.
Visualization Type	<ul style="list-style-type: none"> • Data cards: summarize the number of projects, amount of lending, and the number of countries and sectors supported. • Text: reinforces The WB missions and explains a little about the institution.

Table 3.4 - Content of V1 (part 1)

Visualization	V1 - Map
Main Message	<p>How the World Bank expanded its lending projects around the world through time.</p> <p>The countries where any project was approved are highlighted with a color that represents the amount of investment. That way it is possible to notice the increase of different countries supported and the increase in the amount of lending.</p>
Visualization Type	<p>Choropleth Map: This visualization was chosen to represent a quantitative attribute (amount of lending), taking advantage of the geographical attributes the dataset provided;. The map allows to visualize countries that received more or less lending and the evolution in the number of countries supported.</p>
Marks	<p>Areas that encode each country.</p>
Channels	<ul style="list-style-type: none"> • Magnitude channel: color saturation. The saturation encodes the amount of lending, where red presents the maximum amount and light orange the minimum amount. • Identity channel: spatial region, as there categorical attributes (countries) and it is possible to use the geographical data to encode the countries using their location in the map.
Interactions and Data Filtering	<ul style="list-style-type: none"> • Filter the year range: using a slider or inputting the years to filter. There are instructions on how to use it. • Filter project sectors: manual filter where the user can click in one or more project sectors to filter. There are instructions on how to use it. • Animation: a play axis shows an animation that is automatically updated after choosing the year range. The feature allows the user to pause or stop the animation, as well as, go forward or backward year by year manually. The play/pause/stop/forward/backward buttons invite the user to engage with the visualization, as suggested by Blascheck et al. (2019). • Tooltip: When passing the mouse over a colored country, a tooltip shows the name of the country and the percentage from the total of lending by each institution and by both together. • Text: offered context and guidelines for the user to look where the main changes happened in each period.
Tasks	<ul style="list-style-type: none"> • In a chosen year, compare one country with another two countries and evaluate whether the first country received more or less lending than the other two. • Considering South America for all years, which country received more lending. • Between a defined time range, what country received more lending in a specified sector.

Table 3.5 – Content of V2

Visualization	V2 - Lending Entities
<p>Main Message</p>	<p>There are 2 main institutions sponsor The WB’s projects. Each one of them has different target countries and regions to assist.</p> <p>This visualization aims to showcase that the lending provided by each institution is faithful to the institutions’ mission.</p>
<p>Visualization Type</p>	<ul style="list-style-type: none"> • Bubble Chart: this chart encodes 3 different attributes: the lending by each institution (2 quantitative attributes) and the supported regions (categorical attribute). It was opted to not use the size as an encoding. The disposition of each region bubble in the x and y-axis makes it easier to understand what institution lends more money to the region. • Line Chart: this chart is an additional chart to evaluate the lending by each institution throughout all years with a different approach. There are 2 lines represented, each line is an institution.
<p>Marks</p>	<ul style="list-style-type: none"> • Bubble Chart: the information is encoded by points (bubbles). Each point represents a region. • Line Chart: the marks are points connected with lines. The points encode the amount of lending for each year and the lines show a gradual transition from one point to the next and emphasize order.
<p>Channels</p>	<ul style="list-style-type: none"> • Bubble Chart: the magnitude channel is the position on a common scale, where the distance from the x and y-axis represents the amount of lending by each institution. The identity channel is provided by the color hue. Each region has its color and regions that are sponsored mainly by one institution have the same hue, with different saturations. • Line Chart: the magnitude channel is the position on a common scale, where the distance from the x and y-axis represents the amount of lending by each institution. The color hue is the identity channel and each institution has one hue. The color for the institution matches the regions’ color in the bubble chart, following the Gestalt principle of similarity.
<p>Interactions and Data Filtering</p>	<ul style="list-style-type: none"> • Filter: slider that allows the user to choose the year range of analysis. The user can also input manually the year to analyze. The visualization counts with the average lending for each institution in the selected year range. After the range is defined, the average in visualization is automatically updated. • Animation: there is a play axis that allows animation. The animation is updated according to the selected year range. This feature is interesting as it is easy to see the patterns in lending throughout the years. The play button invites the user to engage with the visualization, as suggested by Blascheck et al. (2019). The user can use the animation axis to manually select a year for analysis. A drawback in this interactive feature is that the Power BI settings do not allow the play axis to be more emphasized on the page. • Tooltip: When passing the cursor above the bubbles, a tooltip appears. This tooltip contains the name of the selected region and a line chart that shows the amount lent by each institution through all years for the region.

Table 3.6 - Content of V2 (part 2)

Tasks	<ul style="list-style-type: none"> • What does it mean when a point is above the horizontal dashed line. • Between a specified year range, which of the option received more lending from one of the institutions. More than one option was correct, and the question highlighted this option. This question could be answered by using the animation or by evaluating each region's tooltip. • Between a specified year range, for each year, answer if a specified region received more lending from one institution than another region. This question was elaborated on trying to force the user to take advantage of the play axis possibilities (play the animation or manually setting each year). However, it was also possible to use the slider to filter each year.
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Table 3.7 – Content of V3 (part 1)

Visualization	V3 - International Scenery Impact
Main Message	<p>This visualization aims to illustrate to the User how the international scenery impacts the allocation of resources and approval of projects. Another intention was to show that the changes in approved projects or budget allocation agree with The WB missions and that the institution's presence increases when events as pandemics or economic crisis emerge. Because of that, it has a more author-driven approach, as the intention is that the user primarily follows the author's narrative. The information brought by this visualization is provided by The World Bank's annual reports and researches of important events in the selected years.</p> <p>The visualization takes advantage of color as a pre-attentive attribute. Four years were select to illustrate the message the visualization brings, thus the points/bars related to those years have different colors than the others.</p> <p>The use of both bar and line charts for representing one qualitative and one quantitative attribute without using a secondary y-axis with different units was inspired by Cole (2015). The author uses the alternative to pull the graphs apart vertically, separating the y-axis and keeping the same x-axis. According to the author, this approach focuses on the overarching trends.</p>
Visualization Type	<ul style="list-style-type: none"> • Bar Chart: shows the trend of the total amount of approved lending over time since 1970. The use of pre-attentive attributes can be seen here. • Line Chart: shows the trend of the total amount of approved projects over time since 1970. The use of pre-attentive attributes can be seen here. The line chart is a common approach to visualize time-related attributes. • Slope Chart: emphasizes a before and after view, emphasizing the changes from one year to another in selected categories.

Table 3.8 – Content of V3 (part 2)

<p>Marks</p>	<ul style="list-style-type: none"> • Bar Chart: lines aligned in a vertical position. • Line Chart: points connected with lines. The points encode the number of projects for each year and the lines show a gradual transition from one point to the next and emphasize order. • Slope Chart: similar to the line chart, the marks are points connected with lines.
<p>Channels</p>	<ul style="list-style-type: none"> • Bar Chart: the magnitude is encoded by the length of each bar. The identity channel is the spatial position as the categories are separated by the vertical position of bars. Due to the use of pre-attentive elements, the color hue is also an identity channel. • Line Chart: The magnitude channel is the position on a common scale. The identity channel is spatial position, where the vertical and horizontal positions indicate different quantitative attributes (number of projects and year, respectively). The use of color is also an identity channel due to the use of pre-attentive elements. • Slope Chart: again, similar to the line chart, this chart uses spatial position and color hue as the identity channel. The use of color hue is noted as an identity channel, as each category was assigned with a color. The magnitude channel is the position on a common scale.
<p>Interactions and Data Filtering</p>	<p>Tooltips: pop out when passing the cursor above an information point. This interactivity was explained in a short text along with the context of the visualization to incentive the user to use the feature. The choice to insert an information point was another tentative to suggest interactivity to the user. The tooltip shows the slope chart with information of yearly total lending in project sectors that showed a considerable increase in the amount in lending from one year to another. This increase is possibly related to the current international scenery and supports the message the visualization is trying to communicate.</p>
<p>Tasks</p>	<ul style="list-style-type: none"> • Which year had the highest amount of approved lending and which year had the highest number of approved projects. • In a specified year, which sector had the highest increase in approved lending – it was mandatory to use the tooltip. • Based on the information shown, whether the user agrees that the international scenery could influence the approved projects.

Table 3.9 – Content of V4 (part 1)

Visualization	V4 - COVID-19
Main Message	<p>The COVID-19 pandemic affected The WB projects. This visualization aims to understand how the COVID-19 Fast-Track Facility impacted the allocation of projects and which regions were priorities for COVID-19 related projects.</p>
Visualization Type	<p>The proposal to this visualization was to serve as a dashboard. Dashboards are used as a strategical, integrated, and informed navigation tool for policymakers and the design is usually based on ad-hoc considerations and different visual features are used to show data in a graphical form (Kourtit & Nijkamp, 2018; Nadj et al., 2020). With this intention in mind, different types of visualizations composed this page:</p> <ul style="list-style-type: none"> • Heatmap: the heatmap is useful to compare trends over time, seasonality, and spot outliers. The aim of using this visualization was to show a time analysis comparing the number of approved projects in each month of 2020, related or not with COVID-19 initiatives. • Waffle Chart: to show the users an unusual visualization, the waffle chart informs the percentage of 2020 approved projects related to COVID-19 initiatives, concerning all approved projects during the year. • Bar Chart: This chart shows the number of COVID-19 approved projects by region. The bar chart is appropriate in this case because it can encode one categorical attribute (regions) with its respective quantitative attribute (number of projects) and it is easy to compare the categorical attributes. The horizontal orientation was chosen to increase the readability of labels. • Pie Chart: the pie chart brings a rough distribution of the amount lent by each institution. It also encodes one categorical attribute (institution) with its respective quantitative attribute (amount of lending). The use of this chart is interesting as it is a very popular visualization and most users are used to it. However, it is not that simple to make comparisons, especially when there are many categories represented. On the other hand, it can be useful when showing that one portion is relatively bigger/smaller than others and highlight this occurrence. To improve understanding, and following best practices, there are labels next to each slice. • Data card: this visualization shows the number of different countries supported by the initiatives.
Marks	<ul style="list-style-type: none"> • Heatmap: the number of projects in each month is encoded with each compartment area • Waffle Chart: the percentage of projects is encoded with its proportional area • Bar Chart: each bar is represented by a line and represents the number of projects for each category • Pie Chart: the mark for this visualization is the area (wedges)

Table 3.10 – Content of V4 (part 2)

<p>Channels</p>	<ul style="list-style-type: none"> • Heatmap: the magnitude channel is color saturation and the identity channel is spatial position. Regarding the colors, light blue indicates a lower number of projects, while red is the highest number. The spatial position is used as the values are ordered by month and by project directly related or not to COVID-19. • Waffle Chart: this chart encodes data with the area (magnitude) and color hue (identity). Each circle represents 1% of the total and each category (COVID-19 related project or not) is assigned with a color. The area represented by each circle color is the percentage number of projects. • Bar Chart: the magnitude is encoded by the length of each bar. The identity channel is the spatial position as the categories are separated by the vertical position of bars. • Pie Chart: the magnitude is encoded by both angle and area – the user can choose how to interpret it. The identity channel is the color hue, as each category is assigned with its color.
<p>Interactions and Data Filtering</p>	<p>The visualization design divides the page into 2 parts.</p> <ul style="list-style-type: none"> • Left side (heatmap and waffle chart) Tooltip: when passing the cursor over the heatmap, a tooltip appears with information regarding the number of projects in each month. • Right side (bar and pie chart, and data card) Filter: the slicer allows choosing all, one or more project sectors to analyze the number of countries in total that received lending for the selected sector(s) in COVID-19 related projects in 2020. By clicking in the region, on the bar chart, the data card filters the number of countries supported in the region. There is instruction on how to filter the slicer, but the filtering in the bar chart proposedly didn't have any explanations, aiming to evaluate if the users would try to interact with it without needing indications.
<p>Tasks</p>	<ul style="list-style-type: none"> • In which month there was the highest amount of COVID-19 related approved projects. • In which region there was the second-highest number of approved projects in a specified sector. • How many countries in a specified region received lending – this question was formulated to evaluate if the user would remember to remove filters and if the user would proactively look for other ways to interact with the visualization. • If a specified institution supported more projects in 2 specified sectors than the other.

4. RESULTS

4.1. PROTOTYPE

The first result of this study was the prototype. Thus, before starting to analyse the results from the experiment, the visualizations can be seen on the link: <<https://bit.ly/3fRioYl>> and in the screenshots below (Figure 4.1 to Figure 4.4).

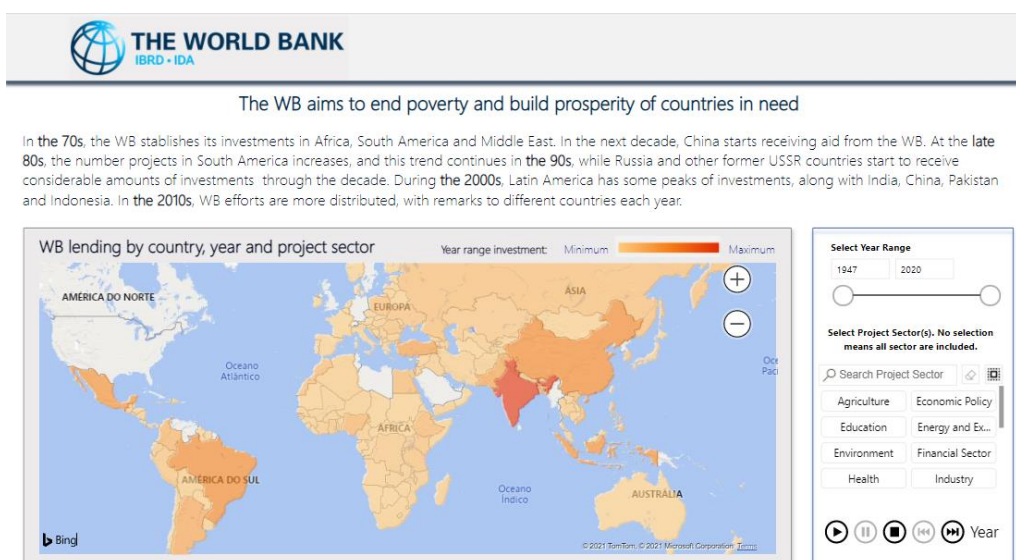


Figure 4.1 – Prototype V1

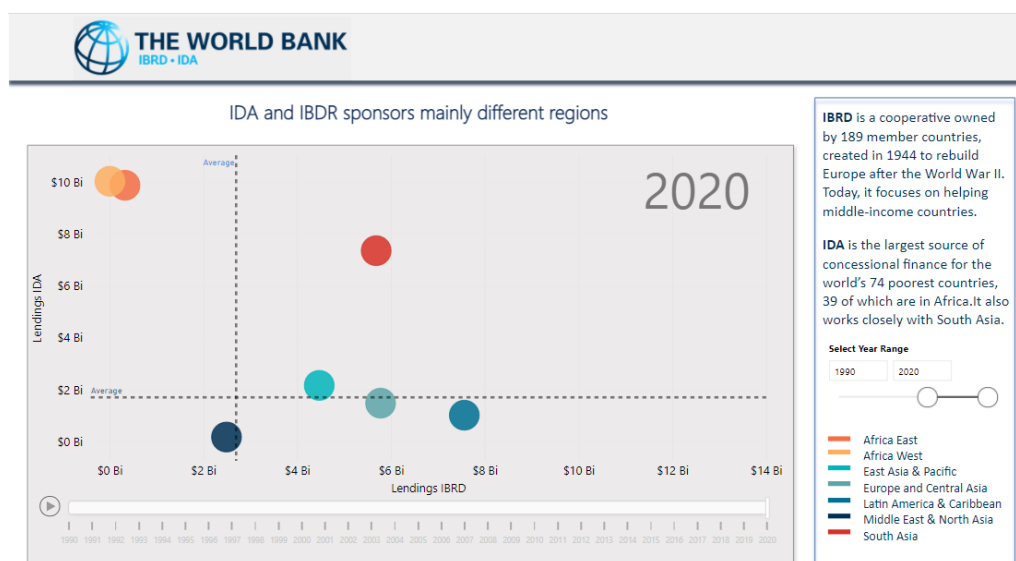


Figure 4.2 – Prototype V2

The international scenario impacts projects and lending allocation

The WB missions are to **end poverty** and promote **shared prosperity** by increasing countries' income. To accomplish this, **the international scenario** plays an important role to define where to allocate resources and what projects to approve.

Pass the mouse over the **i** icon, you can learn what events motivated changes or increases in sponsored projects.

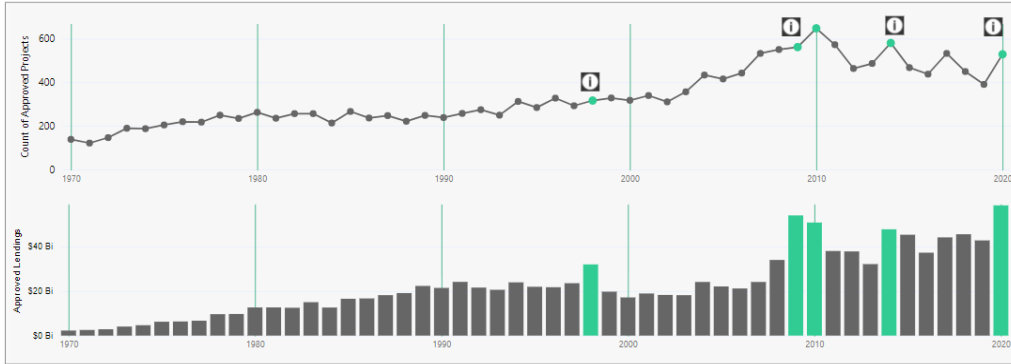


Figure 4.3 – Prototype V3

The WB has mounted the fastest and largest crisis response in its history.

On April, the first group of projects using the **COVID-19 Fast-Track Facility** was approved.

Beyond **health** and **education**, the WB focus on **job creation** and **strengthening institutions and policies**.

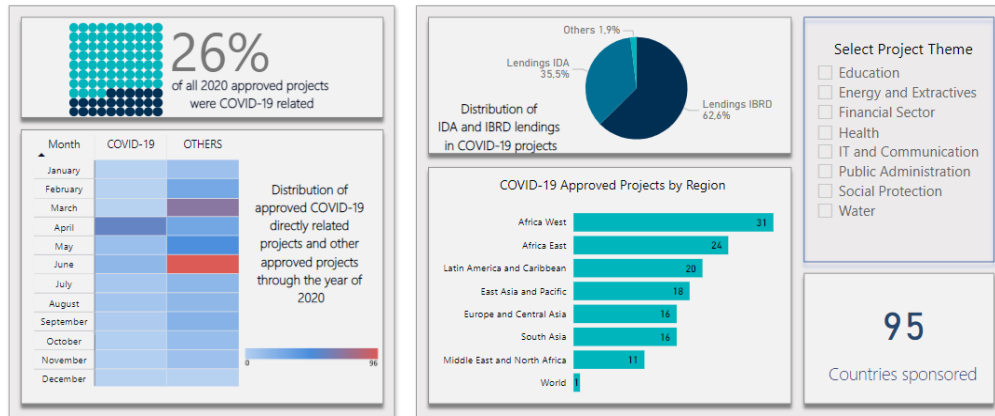


Figure 4.4 – Prototype V4

4.2. SURVEYS RESULTS

The survey was posted online via the software Qualtrics and received answers from February 24th until April 6th, 2021. There was a total of 94 valid answers. The answers from the User Profile survey defined

the level of visualization literacy and to which group the individual would belong. The group of users with a high level of literacy was called Experient, while the other, non-Experient.

It was expected that users could have a biased or different understanding of their “expertise”, therefore the user could not self-assess their literacy level. When developing the questionnaire there was a doubt if the user’s study background and current occupation would be sufficient and reliable enough to divide the groups. Because of that, in the User Profile questionnaire, technical questions were proposed and the sentiment when using data visualization on daily tasks was inquired.

When comparing the 3 types of questions (background, technical and daily tasks) there were some conflicts. For example, users who currently work with data analysis or visualization, but aren’t familiar with more advanced visualizations, or aren’t aware of the concept of outliers. There was one user that claimed to work with data visualization but wasn’t comfortable using visualization on websites or newspapers. Other users affirmed being able to understand the proposed visualization examples but were neutral about their feelings on being able to answer questions based on visualizations. Another inconsistency was users that had knowledge of a great number of visualization types but were not familiar with the concepts of outlier and/or correlation, or didn’t feel comfortable using visualizations to answer tasks, thus not being classified as Experient because it was understood the person recognized the charts but wasn’t capable to interpret and use it with ease.

The Experient group should be composed of users with a high level of visualization literacy skills. Therefore, because of the above considerations, the groups were divided based on some criteria. To belong to the Experient group, the user must have:

- Answered the number of visualizations types the person is familiarized with equal or greater than 7.
- Answer to the questions “When you read articles from newspapers or websites, do you prefer the information to be accompanied by graphic visualizations?”; “How easy do you find to understand these visualizations?” and “Can you answer questions based on the information obtained through visualizations?”, at the same time, one of the 2 most positive responses.
- Affirmed familiarity with the concept of outlier and methods of identifying it through visualizations.
- Affirmed to be able to find correlations through visualizations.

Based on those criteria, 52 users were considered non-Experient (55%) and 42 were considered Experient (45%).

To understand more about the users’ profile and to find possible limitations for the work, basic descriptive statistics were concluded for each group. Both groups were formed mostly by people between 21 and 30 years. In the Experient group, less than 15% of users are older than 41 years, and this amount increases to 25% in the non-Experient group (Figure 4.5). Moreover, both groups had

mostly users with bachelor's, master, or postgraduate degrees (Figure 4.6). Concerning users' current work, non-Experient users presented a more diverse range of positions, including lawyers, psychologists, professors, dentists, architects, and illustrators. The Experient group had almost 40% of individuals working in data-related fields (Figure 4.7).

Due to the criteria to define which users would be in the Experient group, all users in the Experient group knew the concepts of outlier detection and correlation. In the Non-Experient group, almost 62% of users did not know what an outlier was and 25% knew the concept but not how to find it using visualizations. Almost 10% said they could not find correlations through visualizations.

Age by group

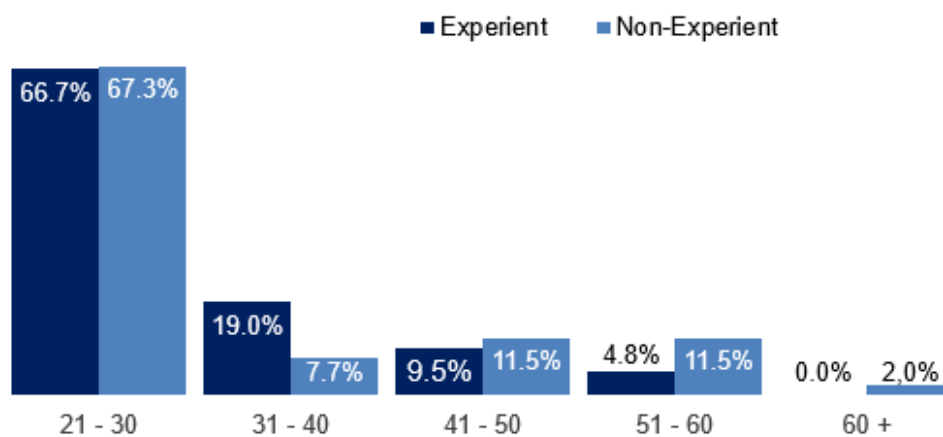


Figure 4.5 – Age by group

Scholarity by group

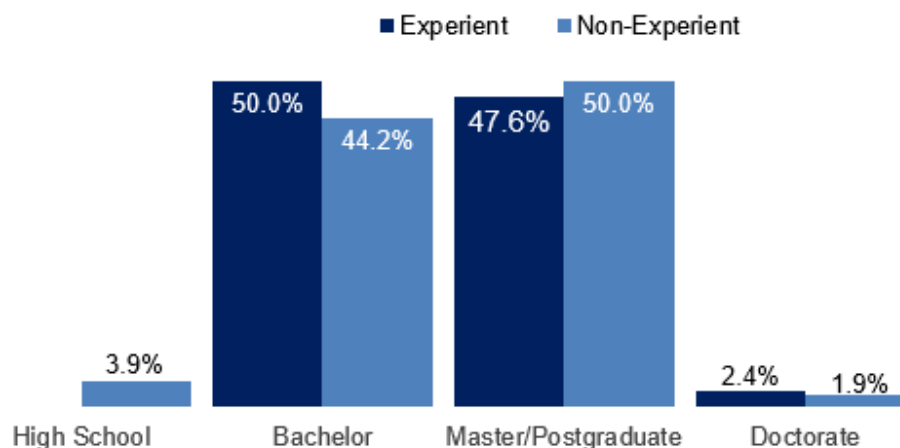


Figure 4.6 – Scholarity by group

Current work by group

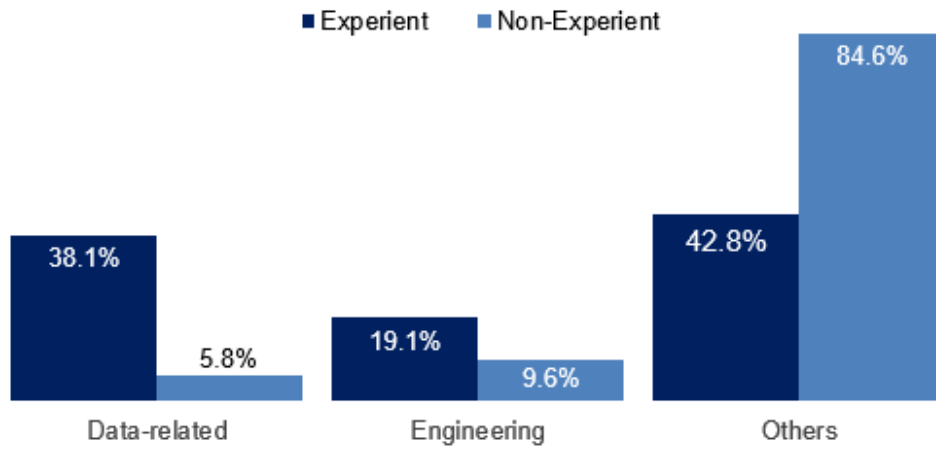


Figure 4.7 – Current work by group

The median number of different visualizations types the Experient group is familiar with is 13, while the non-Experient is 8 (Figure 4.8). It is important to highlight that the Experient group had a threshold of minimum knowledge of 7 visualizations. When showing some types of visualizations, 74% of users from the Experient group affirmed they recognized all visualizations and could interpret them with little additional information, while 75% of non-Experient users say they recognized some of the visualizations and believe they were able to interpret them with little additional information.

Median number of known visualization types

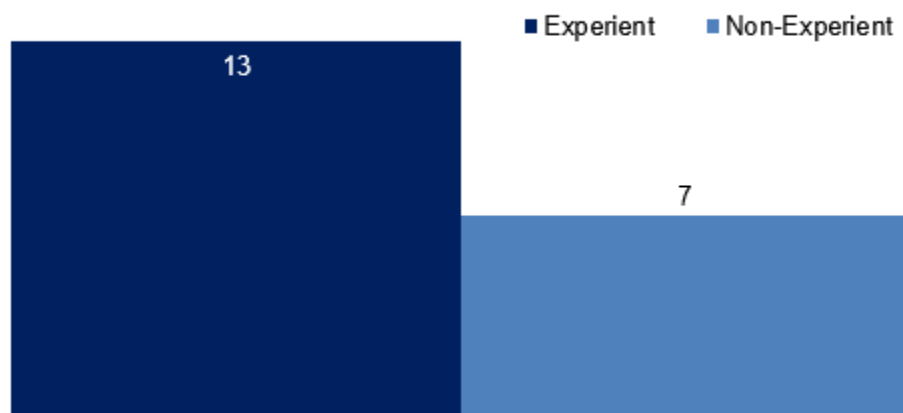


Figure 4.8 – Median number of known visualization types

The multiple-choice questions were made with a 5 point Likert scale and were the following:

- **Q1:** When you read articles from newspapers or websites, do you prefer the information to be accompanied by graphic visualizations?
- **Q2:** How easily do you find it to understand these visualizations?
- **Q3:** Can you answer questions based on the information obtained through visualizations?
- **Q4:** Do you use data analysis and/or visualization in your current job?

Again, the criteria to define Experient users included answering Q1, Q2, and Q3, at the same time, with one of the 2 most positive responses. Non-Experient users mostly responded positively to the use of visualizations in daily tasks, though some users were neutral about those statements or even found it somewhat hard. Concerning the use of data visualization and/or analysis in the current work, 17% of Non-Experient users don't use either, against 7% of Experient users. In addition, around 70% of Non-Experient users affirm to use data visualization in their daily jobs. Thus, a deep knowledge of data visualizations does not depend on user's use of this subject in their current work. More detail can be found on Figure 4.9 and Figure 4.10.

Not-Experient Group

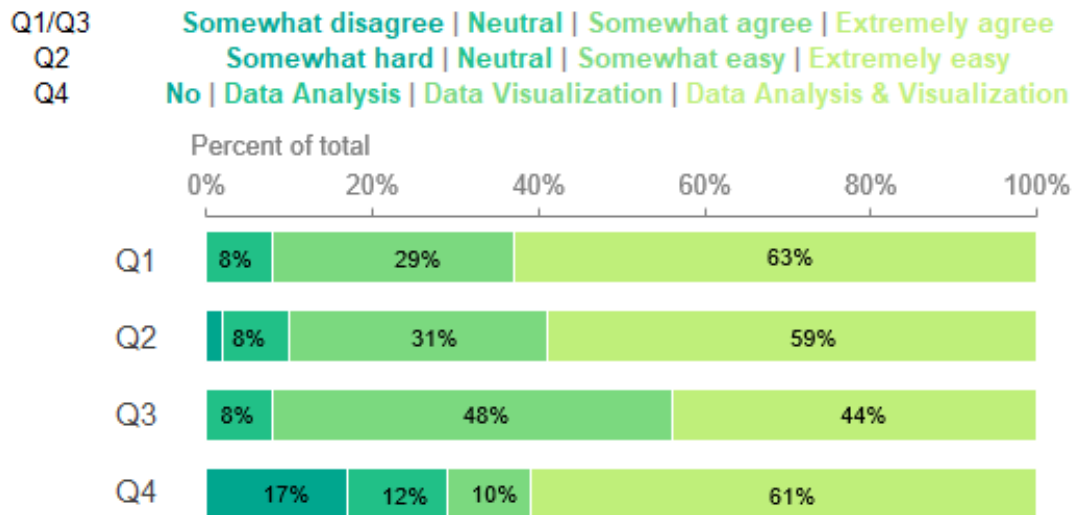


Figure 4.9 – Non-Experient Group multiple choice answers

Experient Group

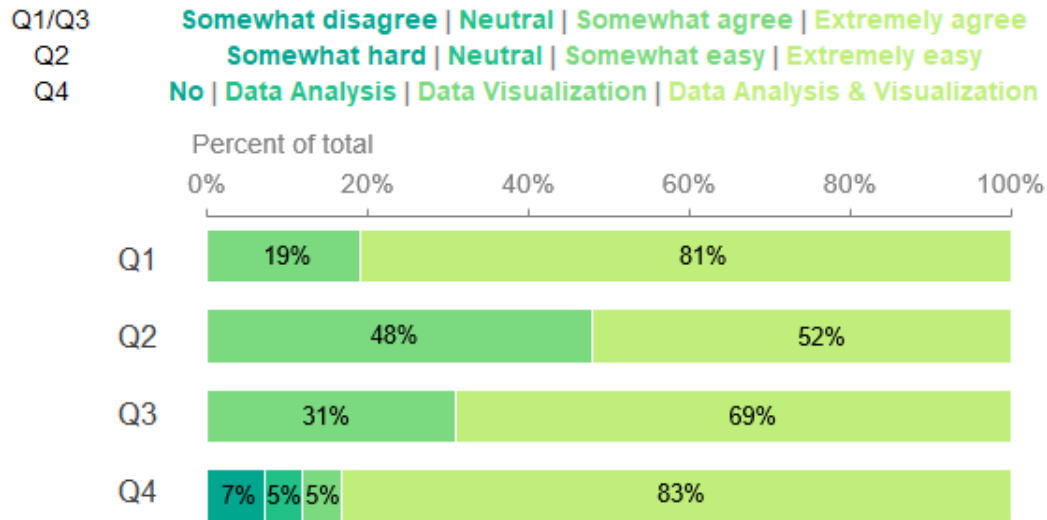


Figure 4.10 - Experient Group multiple choice answers

Quantitative Assessment

- **Accuracy**

The accuracy was defined by calculating the number of correct answers by user and dividing it by the total number of tasks. To classify the result, the final percentage was placed between one of the 4 intervals in Table 4.1.

Table 4.1 – Accuracy interval levels

Accuracy Interval	Level
[0 - 25%]	Very Low
] 25 - 50%]	Low
] 50 - 75%]	Moderate
] 75 - 100%]	High

As expected, the Experient group had an average grading higher than the non-Experient group. The Experient group had an average accuracy of 88.5%, and the non-Experient, an average accuracy of 78.4%. Both groups are in the high accuracy level. Also, 97% of the users in the Experient group had a score of 77% or higher. In the non-Experient group, only 71% of users had a score of 77% or higher, and this group had the lowest grades. Thus, only 3% of Experiment users had a moderate accuracy level, while 21% of Non-Experient users had a moderate accuracy level and almost 8% presented a low level.

Table 4.2 – Accuracy results

Non-Experient			Experient		
Accuracy	Frequency	% cummulative	Accuracy	Frequency	% cummulative
85%	11	21.2%	92%	15	35.7%
77%	10	40.4%	85%	11	61.9%
92%	10	59.6%	100%	8	81.0%
100%	6	71.2%	77%	7	97.6%
62%	5	80.8%	62%	1	100.0%
69%	4	88.5%	31%	0	100.0%
46%	2	92.3%	39%	0	100.0%
54%	2	96.2%	46%	0	100.0%
31%	1	98.1%	54%	0	100.0%
39%	1	100.0%	69%	0	100.0%

When considering the 14 users that scored 100%, 8 of them were Experient (19% of the group) and 6 belonged to the non-Experient group (12% of the group). As it was not possible to join the users when completing the assessment, we cannot be sure of why those users had a higher accuracy. Evaluating each of those user's total time to answer the questions, we notice that average time to complete the tasks for the users in the non-Experient group was 5 minutes higher than the Experient group. Using the ANOVA single factor test, we can verify that the differences in accuracy between groups are statistically significant. The result for the test is on

Table 4.3.

Table 4.3 – ANOVA single factor test for the accuracy measure

SUMMARY

<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>
Experient	42	37.15385	0.884615	0.00757685
Non-Experient	52	40.76923	0.784024	0.02762234

ANOVA

<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	0.2350982	1	0.235098	12.5794782	0.000616	3.944539
Within groups	1.7193901	92	0.018689			
Total	1.9544882	93				

It is possible to extend the analysis to understand which visualization had a bigger impact on the results (Figure 4.11). For all visualizations, the Experient group had a higher average accuracy rate, which

reflects the average prototype accuracy of 88.5% for Experienced users and 78.4% for non-Experienced users. This result was expected as the Experienced group has more knowledge and practice in data visualization.

Average accuracy by group

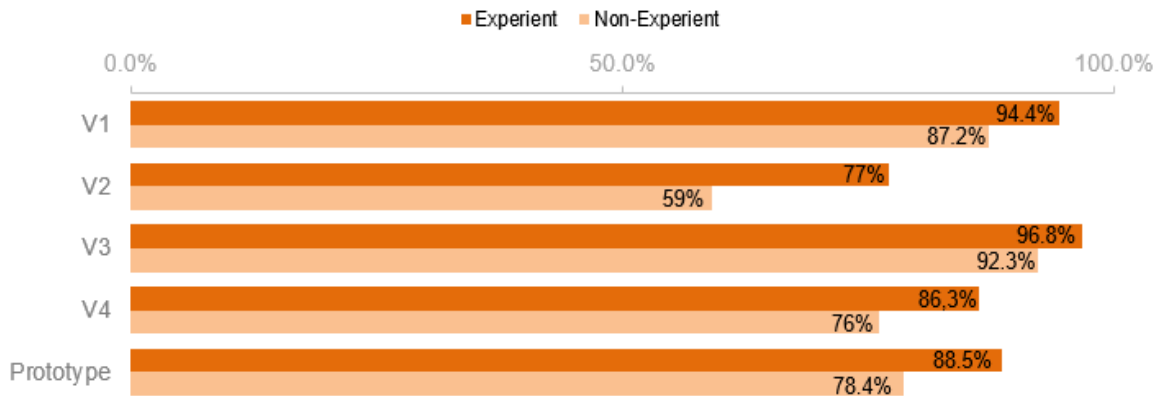


Figure 4.11 – Average accuracy by group

The third visualization (V3) was the one with higher average accuracy for both groups, with both groups achieving more than 90% of accuracy. In addition, it was the visual with the minor discrepancy between groups. Line and bar are common visualization idioms, thus this being a possible reason for the high accuracy levels. Users also had a good performance in V1 but it is noticeable that Non-Experienced users probably had some difficulties analyzing the Choropleth map. For both visualizations, the 2 groups are in the high accuracy interval.

Similar to V1 and V3, in V4 the users' average accuracy was also in the high accuracy interval. V4 presented multiple visualization idioms, including bar and pie charts and heatmap. Considering this evaluation result, users had a similar response to this approach with plenty of visualizations of the same topic.

The second visualization (V2) was the visualization where users probably had more difficulty understanding the chart and answering the questions. It was also the visualization where the groups had the largest average accuracy discrepancy – 77% for the Experienced group and 59% for the Non-Experienced group, leading the Experienced group to be in the high accuracy level and the Non-Experienced in the moderate accuracy interval. This result may indicate that users are not used to dealing with bubble charts and analyzing similar variables in both axes (dollars lent by different institutions).

To have a deeper understanding, the accuracy for each task was also evaluated.

For V1, the questions asked the user to filter years and sectors. Overall, all 3 tasks were similar and it was needed to compare each country's hue or take advantage of the tooltips. There was 1 user from the

Non-Experient that select the choice “I don’t know / It’s not possible to answer” for question 1.1 and another 2 users, one from each group, selected this answer for question 1.2. The first task was a little more complex as asked the users to compare 3 different countries. In addition, it was the first questions users were responding to and possibly still getting to understand the chart, thus, making sense this question had minor accuracy rates. Figure 4.12 shows the results in detail.

Average accuracy by group for tasks in V1

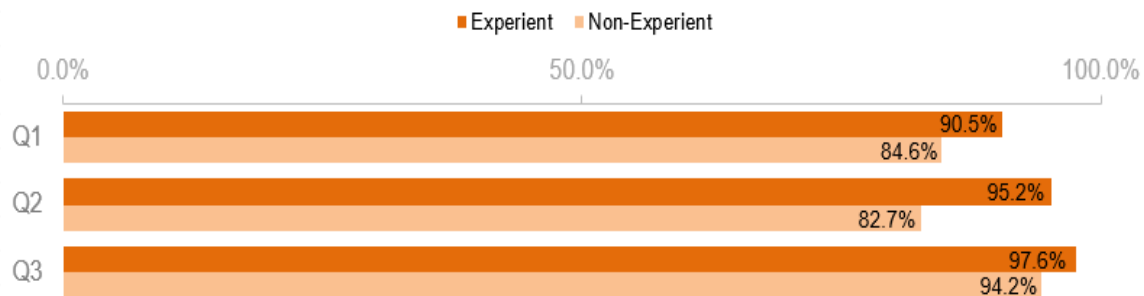


Figure 4.12 – Average accuracy by group for tasks in V1

V2 was the visualization with the lowest accuracy rate. In this visualization, it was important to understand how to read the vertical and horizontal axis, which was the theme for the first question. Experient users had an accuracy rate almost 15% better than Non-Experient users (Figure 4.13).

The second task had 2 correct answers and this possibility was indicated in the task. If we consider users that got 1 correct answer, the accuracy for Experts would rise to 97.6%, and for Non-Experts, 76.9%. Therefore, almost 12% of Experient users chose only one correct answer, while this percentage was 21.2% for Non-Experient users. The third question was the task with the worst accuracy rate for both groups. It is possible that the interpretation of the question was difficult, leading to the wrong use of the year slider. It was asked to evaluate the lendings by year, not a sum of all years, differently from task 2.2. A total of 7 users answered “I don’t know / It’s not possible to answer”, 4 Non-Experient users, and 3 Experient users. Regarding the accuracy interval, both groups were in the low accuracy interval for this question.

The third visualization was created with line and bar charts and obtained the highest average accuracy. This could be explained since those types of visualizations are more usual. The first question was simple and only 1 Non-Expert user answered it wrong. The visualization was developed with pre-attentive attributes, which possibly helped with the task (Figure 4.14).

Task 3.2 used tooltips and a line chart to compare the increase of lendings for each sector and errors might happened due misinterpretation. Finally, question 3.3 was created to understand if the user comprehended the main objective of the visualization – how lending is impacted by the international

scenario. All users that did not respond “Yes” to this question, answered, “I don’t know / It’s not possible to answer”.

Average accuracy by group for tasks in V2

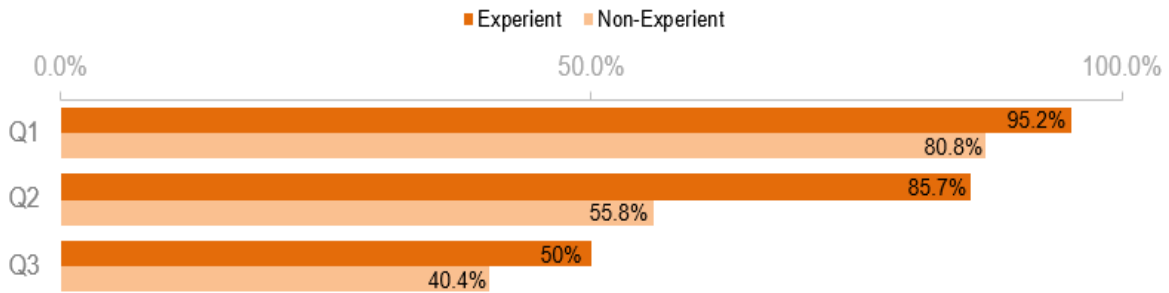


Figure 4.13 - Average accuracy by group for tasks in V2

Average accuracy by group for tasks in V3

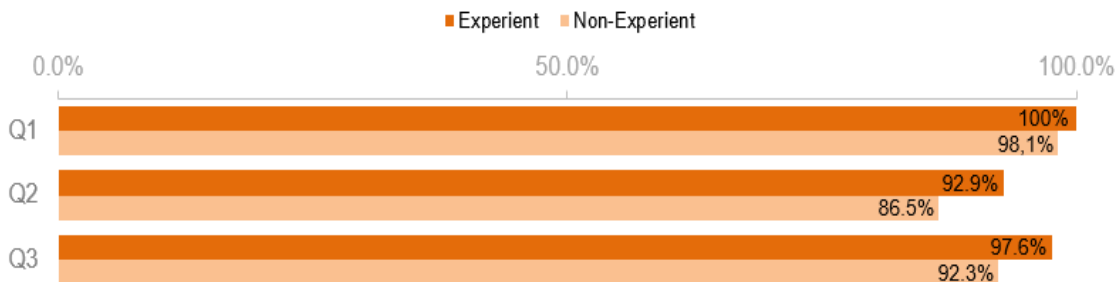


Figure 4.14 - Average accuracy by group for tasks in V3

The last visualization was composed of different types of charts. Task 4.1 asked the users to interpret a heatmap. All wrong answers were the same and it is possible to infer that it was due a wrong interpretation of the question. The task was to evaluate “COVID-19 related projects” and the answer user gave referred to “Other projects”, that had a higher number of projects and, therefore, showed a more distinguished color in the heatmap. Heatmaps aren’t a very usual visualization idiom, so the high accuracy rate for this question for both groups is interesting (Figure 4.15).

The second question needed to use a filter and to evaluate a bar chart. Curiously, this question was the only one where Non-Experient users had a higher accuracy rate. In task 4.3, users had to discover an

interactive element that was not described in the text and was triggered by clicking in a column chart. As expected, Experienced users were more capable to discover interactivity. When analyzing the wrong answers, 29% of Non-Experienced and 19% of Experienced users answered the value of the bar they were supposed to click, while 25% of Non-Experienced and 10% of Experienced users answered: "I don't know / It's not possible to answer". Summing those answers with the users that had the correct response, leads to almost all tested users. Finally, question 4.4 asked to interpret a pie chart and select 2 options in the filter. 5 Non-Experienced users and 2 Experienced users responded "I don't know / It's not possible to answer".

Average accuracy by group for tasks in V4

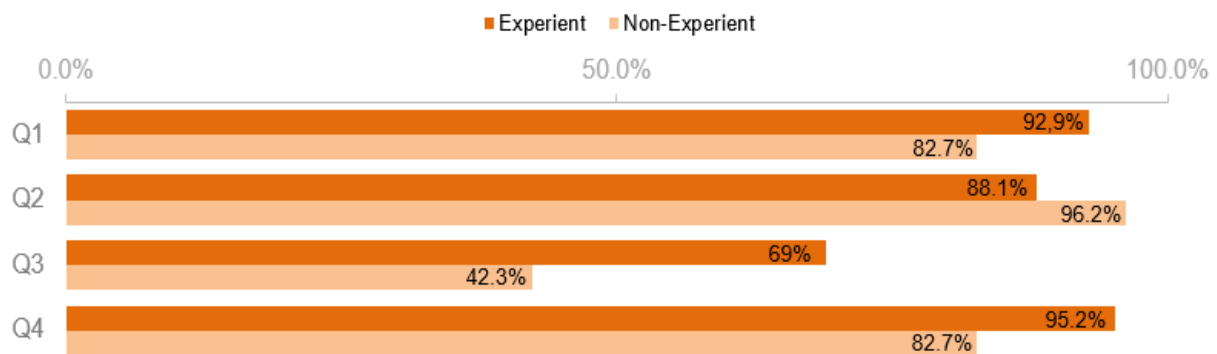


Figure 4.15 - Average accuracy by group for tasks in V4

- **Time to Complete Tasks**

The Qualtrics software allowed to add a tracker that to count the time each user took to proceed to the following survey page. This tool also counted the total clicks performed by the user. In addition, the software offered the total time the user took to respond to all surveys. The tracker was used for all questions in the quantitative assessment. To evaluate the time to complete the tasks with more precision, a sum of the time each user took to submit each answer was performed.

As expected, the Experienced group had a smaller average time to complete all tasks and the group presented an average time almost 37% smaller than the non-Experienced group (Figure 4.16). Also, the variance for the non-Experienced group is more than 6.5 times higher than the Experienced group. The median had a small difference, of only 20 seconds less for the Experienced Group – 999 and 979 seconds, respectively.

According the ANOVA single factor test, the total time to complete the tasks (in seconds) by group is not statistically significant (Table 4.4).

It is also interesting to analyze the time each group took to complete each visualization and each task. For both groups, V4 was the visualization user were able to complete tasks faster. Especially for the Non-Experient group, the time users took was considerably smaller. In addition, V4 presented almost the same total time average for both groups, with an interesting note to the highest time belonging to the Experient group, the only visualization where this trend happened.

Average total time to complete tasks by group (minutes)

Non-Experient users took in average more time to complete the tasks, and the variance was also higher

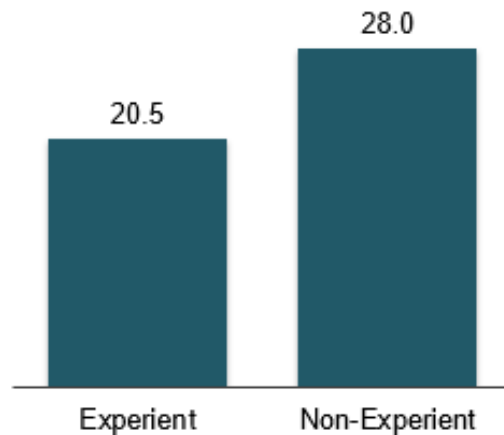


Figure 4.16 – Average total time to complete tasks by group

Table 4.4 - ANOVA single factor test for the time to complete tasks measure

SUMMARY

Group	Count	Sum	Average	Variance
Experient	42	51567.728	1227.803048	1480883.444
Non-Experient	51	86733.468	1700.656235	9861820.013

ANOVA

Source of Variance	SQ	gl	MQ	F	P-value	F crit
Between groups	5149785.738	1	5149785.738	0.846197889	0.360062	3.945694
Within groups	553807221.8	91	6085793.647			
Total	558957007.6	92				

On other visualizations, the Non-Expert group took an average longer time to complete tasks (Figure 4.17). The biggest discrepancy between groups' average time to complete tasks was in V3. For the Non-Expert Group, V3 was the visualization with the highest average total time. This average time was more than double what the Expert group achieved. For the Expert group, users took more time to complete V2 tasks. In this stage, both groups had very similar average times.

Average time to complete tasks by group (minutes)

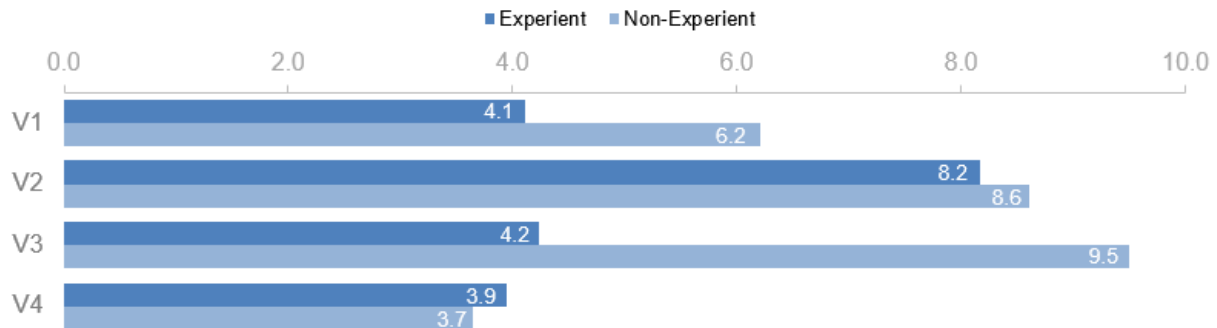


Figure 4.17 – Average time to complete tasks by group

The first task from V1 was the most complex as it was needed to compare 3 different countries and it was the first moment the user got to explore and comprehend the visualization. In addition, this visualization contained the longest introductory text of the prototype, that suggested where the user attention focus should be during each period to be analyzed. This could explain why this task took 3 times or more for users to complete compared to the other 2 tasks. For all tasks, the Expert group was faster to finish (Figure 4.18).

Average time to complete V1 tasks by group (seconds)

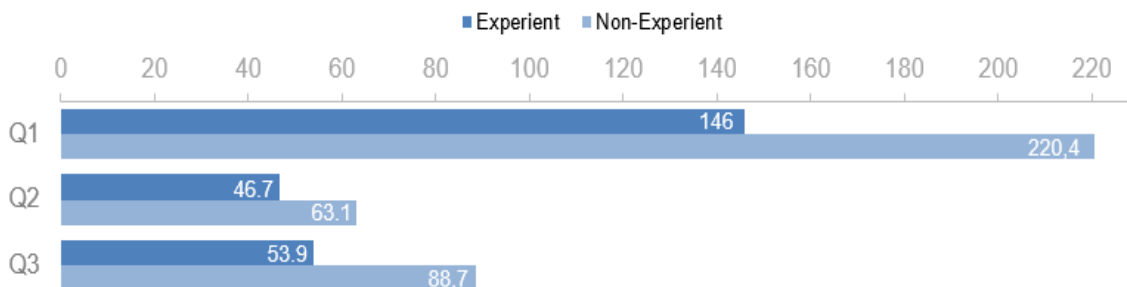


Figure 4.18 - Average time to complete V1 tasks by group

The second visualization showed very different results for both groups in each task. In the first task, the Experient average time was twice the average from the Non-Experient group. It is possible that the Experient group used this time to have a deeper understanding of all elements in the visualization. This could also explain why in the next tasks the group performed considerably faster than the Non-Experient users (Figure 4.19).

Average time to complete V2 tasks by group (seconds)

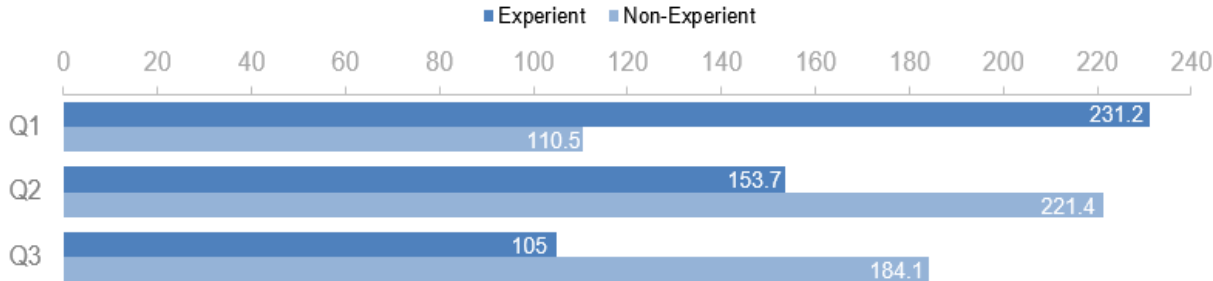


Figure 4.19 - Average time to complete V2 tasks by group

The first task for V3 resulted in very different results for both groups. As it was not possible to accompany the users, it is difficult to understand why Non-Experient users took an average of almost 8 minutes in the first task. There are 2 possible explanations: (1) as in the other tasks in the page, Non-Experient users took less time to answer, maybe those users were more engaged and explored more the visualization, or (2) Non-Experient users had difficulties in understanding and interacting with the tooltips. The third question was concerning the main message the prototype intended to communicate. Judging by the time users spent in this task, the Experient group seems to have taken a deeper analysis to answer the question (Figure 4.20).

Average time to complete V3 tasks by group (seconds)

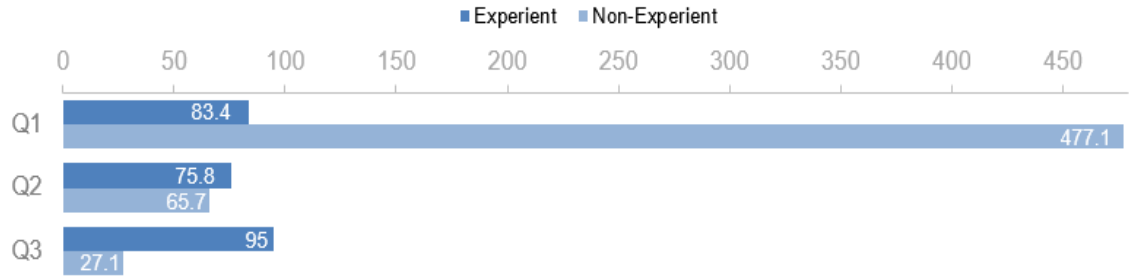


Figure 4.20 - Average time to complete V3 tasks by group

In the fourth visualization, the first task was the fastest question answered by both groups. This question involved interpreting a heatmap, a not very usual visualization type. Likewise the accuracy evaluation, it is interesting to perceive how both groups interact well with the heatmap. The second task was the one where Eperient users took the longest, and 25% longer than the Non-Experient group. This question asked to use a filter and analyze a simple bar chart, so it is strange that Experient users took that long. Maybe it was an issue of interpretation or they spent more time exploring the visual. Next, the users had to figure out a not explicit interaction. Experient users took on average less time in this task and possibly figured out earlier how to answer the question. The final task asked the user to use a filter a interpret a pie chart. Once again, the Experient group took a considerably longer average time to analyze a very usual chart (Figure 4.21).

Average time to complete V4 tasks by group (seconds)

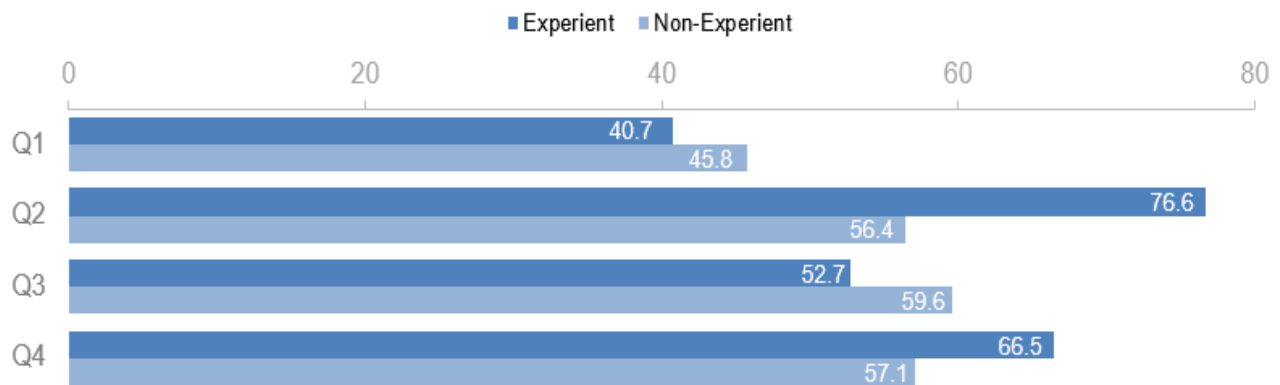


Figure 4.21 - Average time to complete V4 tasks by group

- **Number of clicks**

The total number of clicks will not be evaluated in this work as it is outside the scope and because it was not possible to accompany the user during the survey completion. However, as a suggestion to other studies to further analyze this topic, it was noted that Non-Experient users had a higher number of clicks in almost all questions.

Qualitative Assessment

After completing the tasks, users were asked to qualitatively assess the visualizations. The efficiency assessment was based on the user qualitative assessment on comprehension and perceived information. The utility assessment was made questioning usefulness, complexity, and engagement.

Finally, users were questioned about the effectiveness, to compare this result with the concepts described before.

It is important to highlight that human subjectivity can influence this assessment as users had to use a 5-point Likert scale and each person has its own understanding for each question and for each item on the scale. Also, it is difficult to assess equally the gaps between each item on the scale. The mean of the 5-point Likert scale indicates each measure classification according to Table 4.5.

Table 4.5 – Measure interval levels

Mean Interval	Measure Classification
[0 - 1]	Very Low
] 1 - 2]	Low
] 2 - 3]	Moderate
] 3 - 4]	High

Prototype as a whole

Considering the prototype as a whole, users were asked to assess their level of comprehension of the prototype and the analysis extracted from them. In addition, they answered about the complexity, usefulness, complexity, and utility of the prototype and ranked the visualization according to their preferences. The results are shown on Figure 4.22.

Users' prototype evaluation

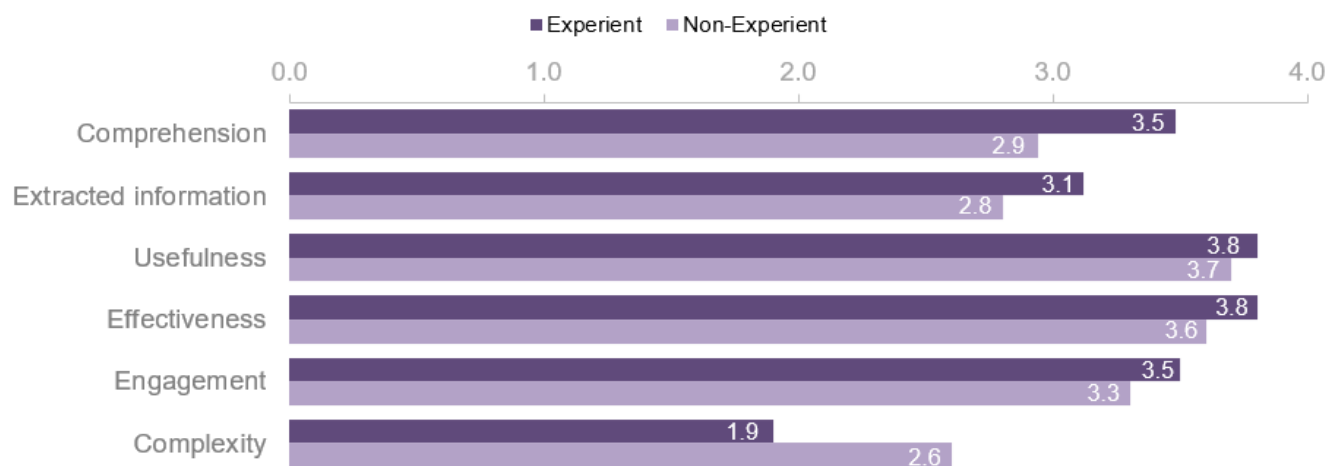


Figure 4.22 – Users' prototype evaluation

Concerning the comprehension and extracted information, the Experient group showed a better performance, but in both cases, the Experient group was within the high interval and the Non-Experient group in the moderate level. When evaluating the complexity, groups had a bigger difference, of more

than 25%. Non-Experient users evaluated the complexity as 2.6 (moderate) while Experient user's average rating was 1.9 (low). Those result makes sense since more experienced users would interpret and gain insights faster and easier than less experienced users. In the usefulness, effectiveness, and engagement assessment, the average results were similar for both groups, with the Experient groups having always an average 0.2 higher than the Non-Experient group and both measures belonging to the high level.

Using ANOVA single factor test, the extracted information assessment was not statistically significant (Table 4.6), while the comprehension evaluation it was (Table 4.7). Regarding the aspects of complexity, usefulness, effectiveness, and engagement, only complexity showed a statistically significant difference between both groups using ANOVA single factor test (Table 4.8 to Table 4.11).

Table 4.6 - ANOVA single factor test for the extracted information evaluation

SUMMARY						
<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
Experient	42	131	3.1190476	0.49767712		
Non-Experient	52	147	2.8269231	0.7341629		

ANOVA						
<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	1.982718	1	1.9827176	3.15331483	0.079079	3.944539
Within groups	57.84707	92	0.6287725			
Total	59.82979	93				

Table 4.7 - ANOVA single factor test for the comprehension evaluation

SUMMARY						
<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
Experient	42	146	3.47619	0.304297		
Non-Experient	52	153	2.942308	0.526018		

ANOVA						
<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	6.622418	1	6.622418	15.50163	0.00016	3.944539
Within groups	39.30311	92	0.427208			
Total	45.92553	93				

Table 4.8 - ANOVA single factor test for the complexity measure

SUMMARY

<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>
Experient	42	83	1.97619	1.438444
Non-Experient	52	137	2.634615	1.256033

ANOVA

<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	10.0725	1	10.0725	7.531828	0.007289	3.944539
Within groups	123.0339	92	1.337325			
Total	133.1064	93				

Table 4.9 - ANOVA single factor test for the usefulness measure

SUMMARY

<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>
Experient	42	161	3.833333	0.142276
Non-Experient	52	195	3.75	0.308824

ANOVA

<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	0.161348	1	0.161348	0.687752	0.409077	3.944539
Within groups	21.58333	92	0.234601			
Total	21.74468	93				

Table 4.10 - ANOVA single factor test for the effectiveness measure

SUMMARY

<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>
Experient	42	159	3.785714	0.172474
Non-Experient	52	190	3.653846	0.505279

ANOVA

<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	0.404022	1	0.404022	1.131828	0.29017	3.944539
Within groups	32.84066	92	0.356964			
Total	33.24468	93				

Table 4.11 - ANOVA single factor test for the engagement measure

SUMMARY						
<i>Group</i>	<i>Count</i>	<i>Sum</i>	<i>Average</i>	<i>Variance</i>		
Experient	42	149	3.547619	0.546458		
Non-Experient	52	176	3.384615	0.829563		

ANOVA						
<i>Source of Variance</i>	<i>SQ</i>	<i>gl</i>	<i>MQ</i>	<i>F</i>	<i>P-value</i>	<i>F crit</i>
Between groups	0.617333	1	0.617333	0.877646	0.3513	3.944539
Within groups	64.71245	92	0.703396			
Total	65.32979	93				

Concerning visualization preference, in both groups, V2 was the least preferred visualization. For the Non-Experient users, more than half of them choose this visualization as the least preferred. An interesting point is that in both groups V4 was chosen by 37-38% of users as the most preferred visualization, but at the same time, it was the second least preferred visualization, chosen by 31% of experienced users and 21% of Non-Experient users. When summing users that selected this visual as their 2 most preferred, both groups had a total of 60% or more of preference for it. V3 was tied with V4 as the most preferred visualization for the Non-Experient group. It was also the second preferred visualization for the Experient group but with a margin of almost 15% less preference to V4. Less than 10% of users in both groups choose V3 visualization as their least preferred.

Overall, the preference for both groups was similar. When evaluating the percentage of users that choose V4 or V3 as the most preferred or the second most preferred visualization, both groups had a total of approximately 60% of preference each. V1 had a slightly minor acceptance for Non-Experiment users as 50% of users choose this visual as the most preferred or second most preferred visualization. This number decreases to 45% for the Experient group. All results are shown on Figure 4.23 and Figure 4.24.

Regarding the other measures, the average usefulness evaluation was very similar for both groups, usually ranging from 3.7-3.8 (Figure 4.25). The evaluation made by the Non-Experient group for V2, was the lowest average of 3.4. Overall, all visualizations had the usefulness evaluation considered as high, for both groups. Concerning effectiveness, users had a similar understanding as to usefulness (Figure 4.26). Once again, V2 was rated with the lowest averages, especially for the Non-Experient group. V1 also had a smaller average evaluation for Non-Experient users. All visualizations had the effectiveness evaluation considered as high, for both groups.

Regarding the engagement, users from both groups also had a similar feeling and an overall high average engagement (Figure 4.27). As in the previous evaluations, V2 was the one with the lowest performance, being the visualization with the same smallest average engagement rate for both groups (3,0). With a slightly better performance, V1 appears with the same rating from both groups too (3,1).

V3 had the same punctuation for both groups (3.3). For the Experient group, V4 had the same average evaluation as V3, so both were considered the most engaging for this group.

Visualization Preference - Experient Group

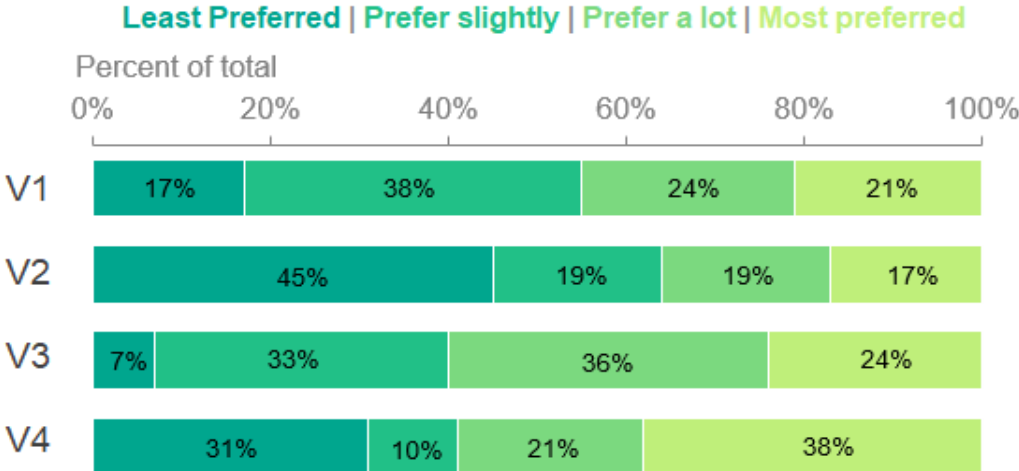


Figure 4.23 – Visualization Preference – Experient Group

Visualization Preference - Not-Experient Group

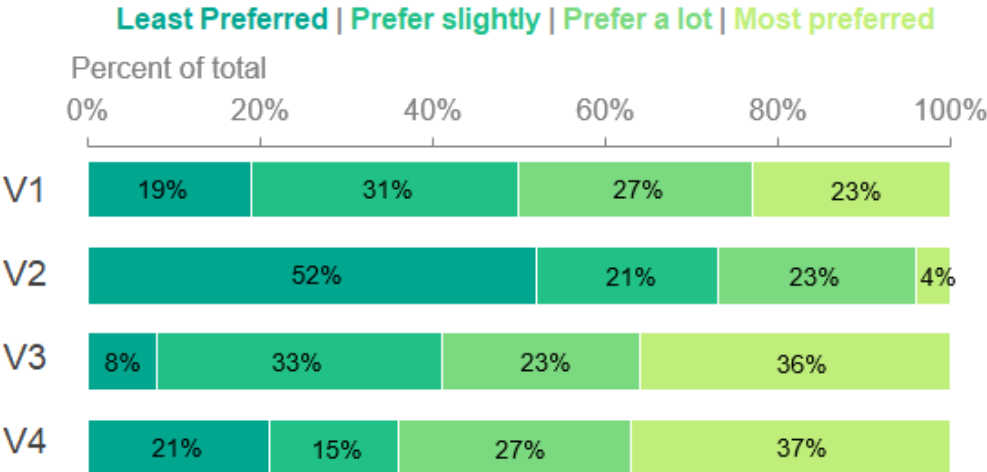


Figure 4.24 - Visualization Preference – Non-Experient Group

A highlight should be made for the V4 Non-Experient group evaluation. In this group, V4 had the highest score from all engagement evaluations, achieving a score of 3.6. This may imply that Non-Experient users are more likely to enjoy visualizations with topics they can relate to and evaluate the impact more easily, such as with COVID-19 information. Also, the use of different idioms on the same page didn't seem to be a problem in users' engagement, even though they aren't experienced individuals; it actually might have increased the engagement and curiosity.

Lastly, the complexity evaluation can offer some insights (Figure 4.28). As expected, the Experient users found the visualizations less complex than the Non-Experient individuals in a meaningful way and the discrepancies in each group evaluation are substantial. Furthermore, the order of complexity was the same for both groups. Following the same pattern as the other items, V2 had the worst assessment, meaning users from both groups found this the most complex visualization. In addition, for both groups, V3 was the less complex visualization, also agreeing with the previous assessments.

It is interesting to note that Non-Experient users found V4 almost as complex as V2, even though they have found V4 very engaging, and V1 was a little less complex than the other two. At the same time, Experient users found V4 significantly less complex than V2 but as complex as V1. V3 was considered of very low complexity for Experient users and low complexity for Non-Experient ones. V1 and V4 wererated as low complexity for Experient users and of moderate complexity for Non-Experient ones. V2 was assessed as of moderate complexity for Experient and Non-Experient users.

A summary with the best and worst results from each evaluated measure is on Table 4.12.

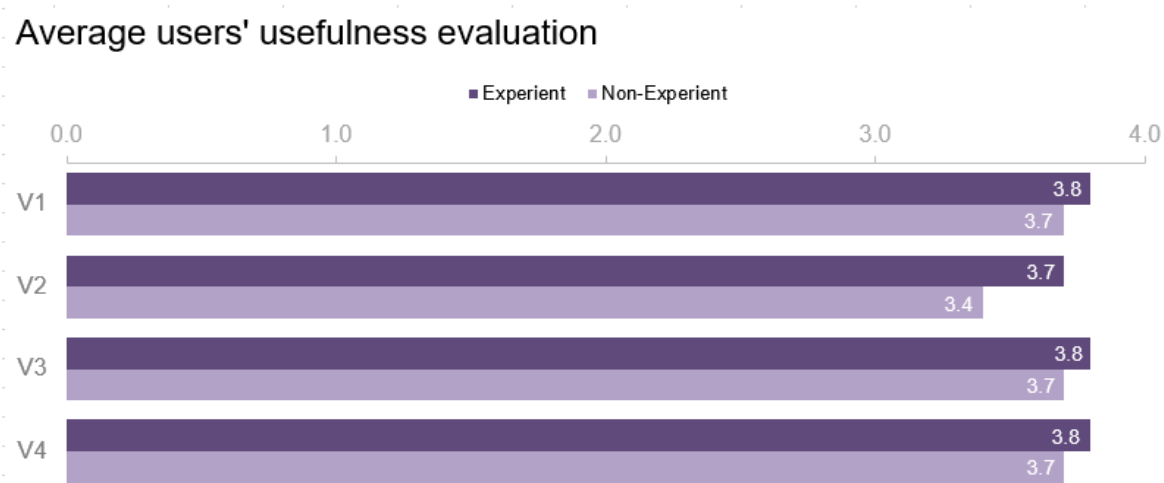


Figure 4.25 – Average user’s usefulness evaluation

Average users' effectiveness evaluation

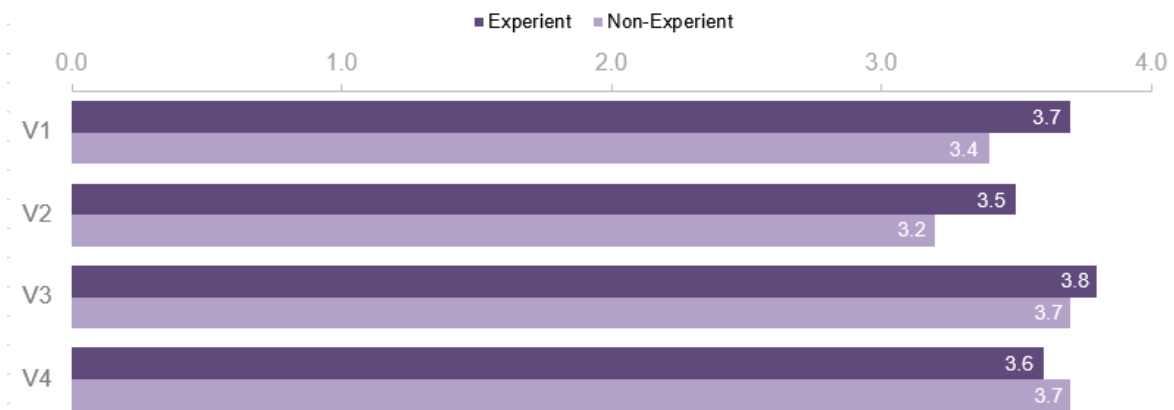


Figure 4.26 – Average user’s effectiveness evaluation

Average users' engagement evaluation

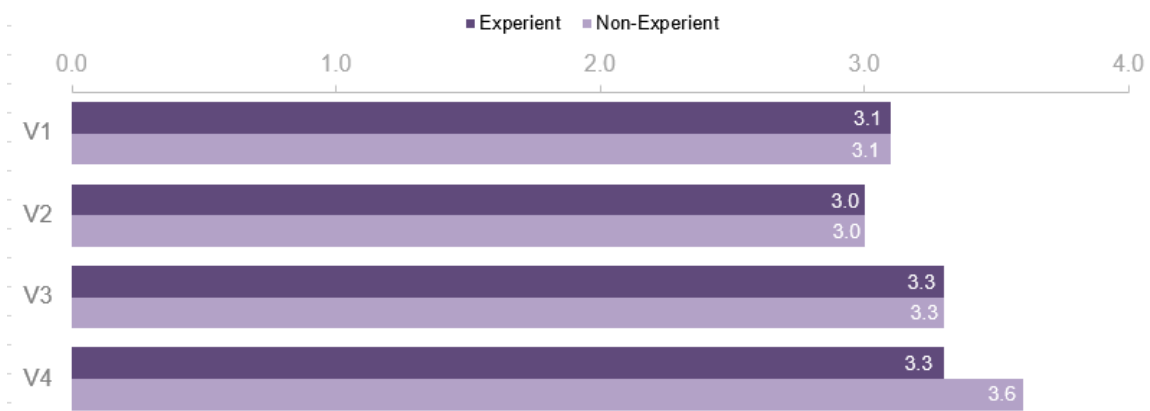


Figure 4.27 -- Average user’s engagement evaluation

Average users' complexity evaluation

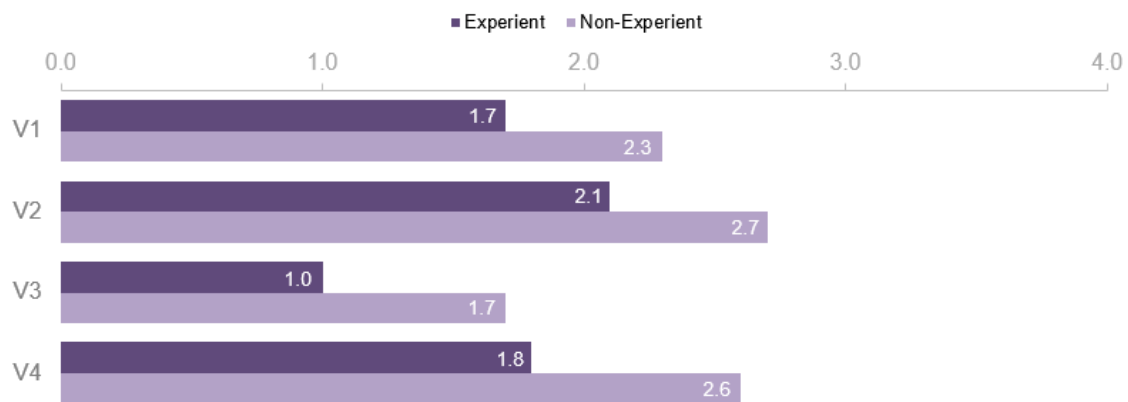


Figure 4.28 – Average user’s complexity evaluation

Table 4.12 – Summary of visualization evaluation measures

Measure	Best		Worst	
	Experient	Not-Experient	Experient	Not-Experient
Accuracy	V3	V3	V2	V2
Completion Time	V1	V4	V2	V3
Complexity	V3	V3	V2	V2
Engagement	V3, V4	V4	V2	V2
Usefulness	V1, V3, V4	V1, V3, V4	V2	V2
Efectiveness	V3	V3, V4	V2	V2
User Preference	V4	V4	V2	V2

Interactive Features

Users were asked about the complexity and usefulness of the interactive options in each visualization on a 3-point Likert scale (Low, Medium, and High). They had the alternative to answer that they didn't use the feature. Some visualizations had the same component so those were evaluated individually for each visualization. The mean of results were classified according to Table 4.13.

Table 4.13 - Measure interval levels

Mean Interval	Measure Classification
[0 - 0.67]	Low
] 0.67 - 1.33]	Medium
] 1.33 - 2]	High

Slider

The slider should have been used to complete tasks in V1 and V2. Considering its complexity users were consistent with the evaluation in both visualizations. Experient users found the tool very simple to use, while Non-Experient users probably had a minor difficulty in using it. About its effectiveness, Non-Experient users kept the same high-level average evaluation for both visualizations but Experient users seem to have found the tool more effective for completing tasks in the first visualization (Figure 4.29 and Figure 4.30).

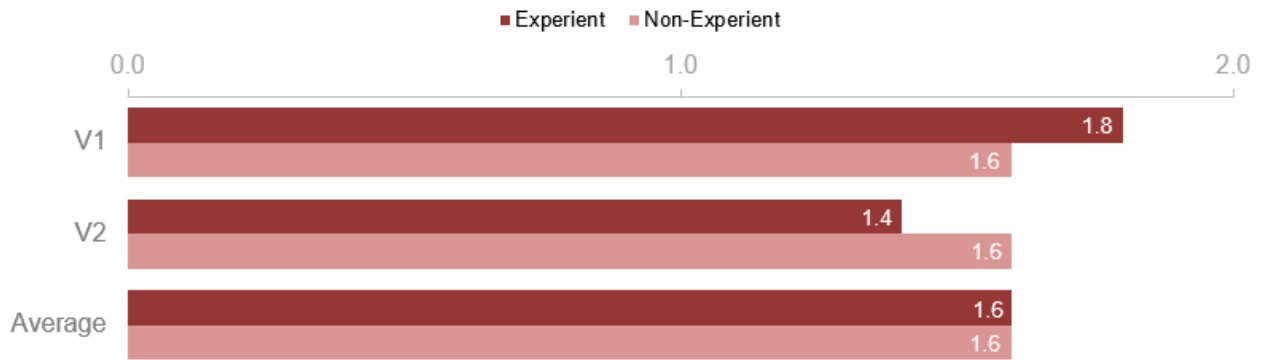


Figure 4.29 – Slider average effectiveness evaluation

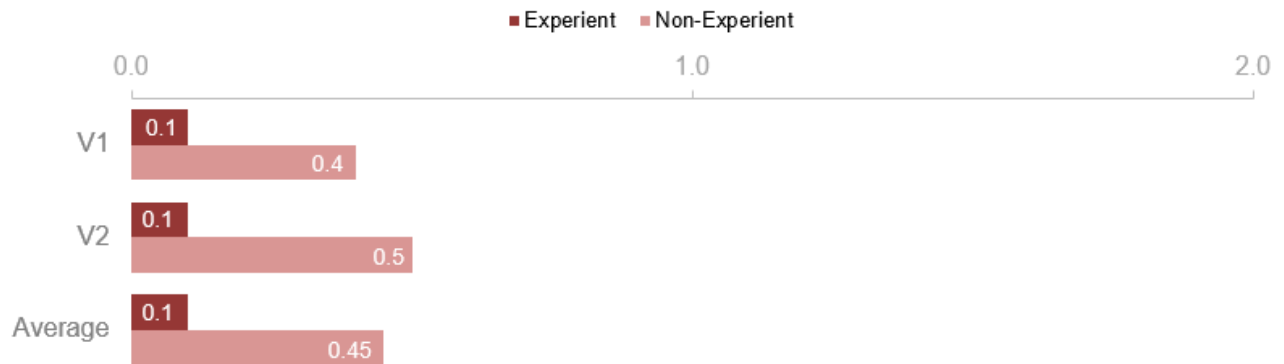


Figure 4.30 - Slider average complexity evaluation

Filter

The filter had the same goal of filtering the project sector in V1 and V4. However, in each visualization, they had different layouts and positioning. Moreover, in V4 there were fewer options to choose from. The average effectiveness is consistently high for both groups and visualizations. Experient users found it more effective but for both groups, the average evaluation was almost the highest possible. Due to the differences in the filter usage, it was expected different results for the complexity. Non-Experient users found the tool a little more complex than Experient users. For both groups, the filter in V1 was more complex, especially for Non-Experient users. This result makes sense as in V1 there were more choices to filter and space was reduced for the number of options, having the user scroll down or use the search feature. (Figure 4.31 and Figure 4.32)

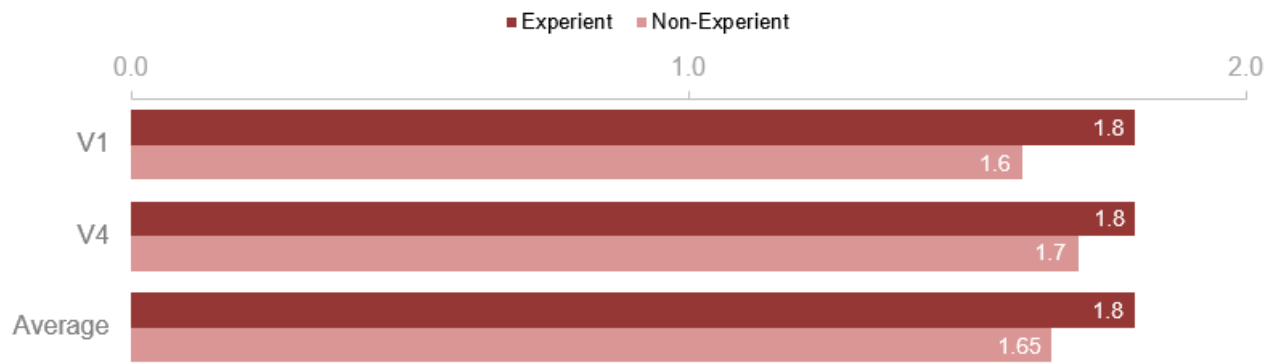


Figure 4.31 – Filter average effectiveness evaluation



Figure 4.32 – Filter average complexity evaluation

Animation

The animation feature was available in V1 and V2, however, it was not mandatory to use it to complete tasks, even though it could significantly facilitate analysis. For each visualization, it was used a different approach and layout for the feature. V1 shown a control option for the animation right below the slider and filter, while in V2 the play axis was below the bubble chart, and a timeline with years was available for the user to slide between years.

The complexity evaluation was consistent for both groups in both visualizations, therefore the 2 applied approaches seem to cause the same impression for users. Non-Experient users found the tool 2 times more complex than Experient users. Regarding effectiveness, for both cases, the Non-Experient users found the animation considerably more effective to answer the questions than Experient users. In V2 the animation was evaluated as slightly more effective than in V1 (Figure 4.33 and Figure 4.34). 38 users (50% of Experient and 33% of Non-Experient users) answered they didn't use the animation in V1, while

31 users (31% of Experient and 35% of Non-Experient) users had the same response in V2.

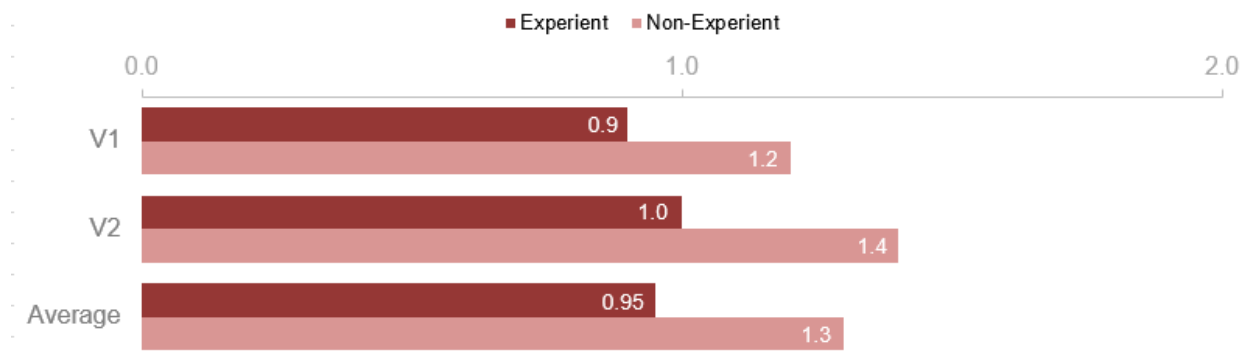


Figure 4.33 – Animation average effectiveness evaluation

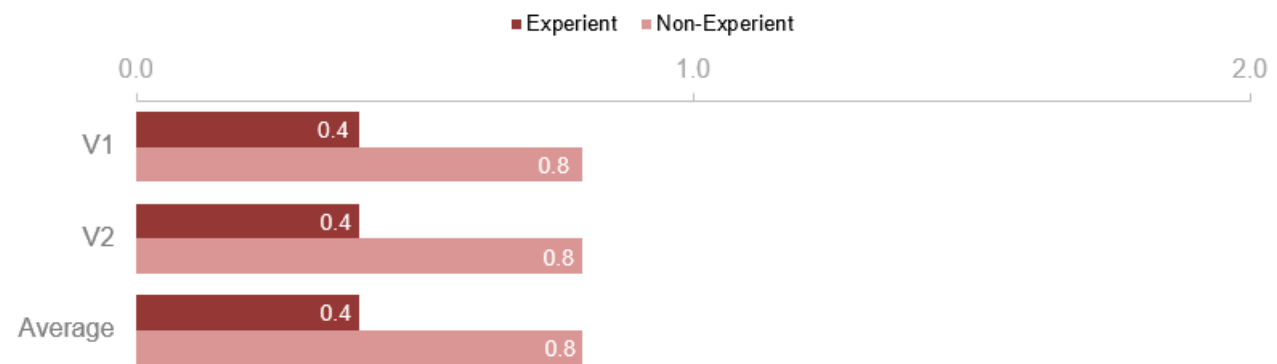


Figure 4.34 – Animation average complexity evaluation

Text

The use of text is important to define the scope and context of each visualization. The users were asked regarding the feature effectiveness in completing the tasks. For Experient users, all texts had similar effectiveness performance, achieving a medium effectiveness level for both groups. Experient users found the text in V3 the least effective. That could be explained by the fact that the text didn't bring much new information and Experient users retained more information from the previous visualization and introduction.

The complexity evaluation was consistent but Non-Experient users found some difficulty on V1 explanations. Agreeing with the complexity assessment for Non-Experient users, they have found the text in V1 a little less effective than in other visualizations. The text in V1 was indeed the longest and containing more information than the other visualizations, as it was intended to guide the user where to focus attention as the animation was played. This could be confusing for Non-Experient users (Figure 4.35 and Figure 4.36).

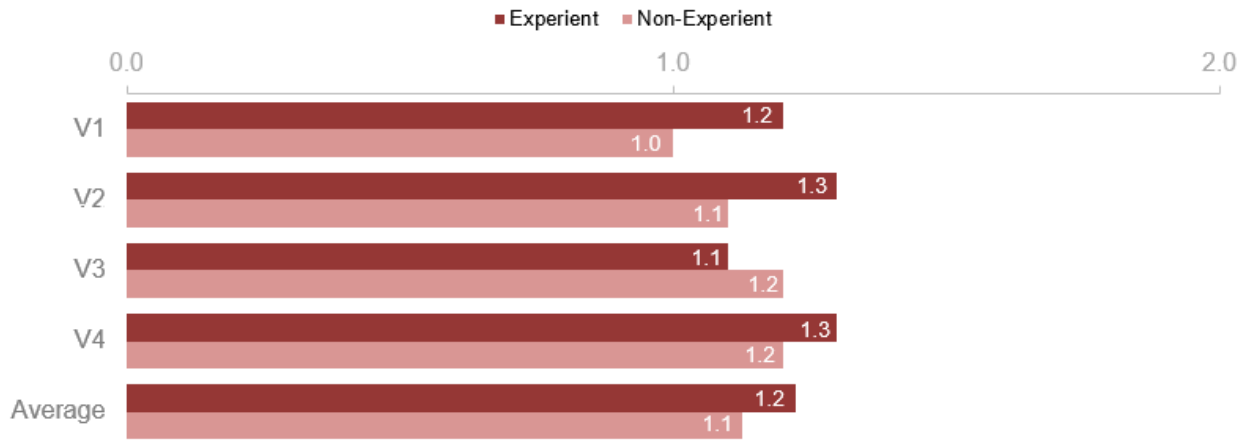


Figure 4.35 – Text average effectiveness evaluation

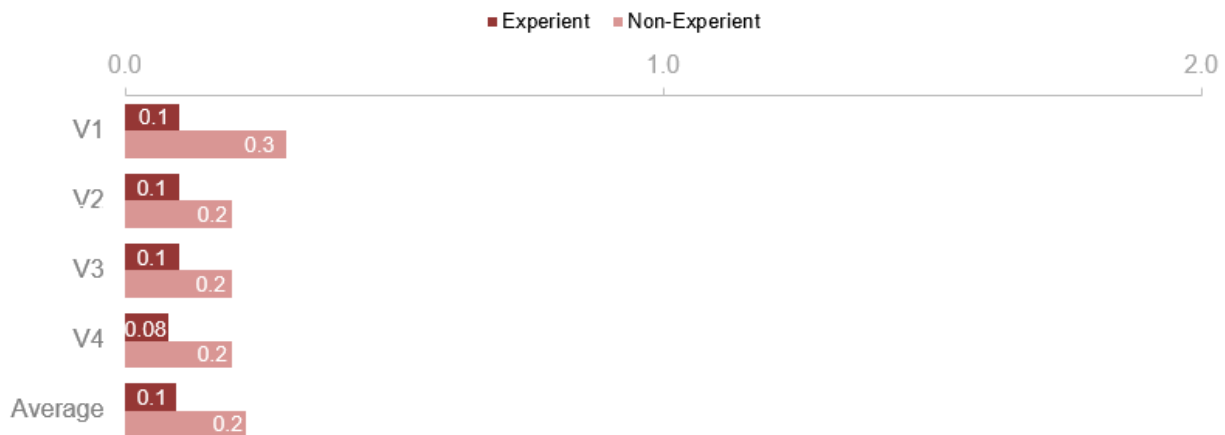


Figure 4.36 – Text average complexity evaluation

Tooltip

There were different types of tooltip in the project. For this section it will be considered only the similar tooltips that appear in V1, V3, and V4, containing information about the variable in which the user passes the mouse over. In V1, the user could pass the mouse over each country and receive information of the total amount of lendings received; in V3.1 the user was able to get information of the actual value of each column or point; in V4.1 the user could see the value of each point on the heatmap and in V4.2 the tooltip showed information about the value of each part of the pie chart.

Once again Non-Experient users found the interactive options more complex. The most complex tooltip seems to be the one used in the choropleth maps. Those tooltips information about the percentage of lendings made by each World Bank institution and the total lending about all lendings for all countries. After a quick interview with a few users, they were confused about the percentages and how they should interpret them to answer the questions. On the other hand, this tooltip was the most useful for both groups. The questions in this visualization could be completed without using the tooltips, using the

color hue of each country, however, users seemed to prefer using the information from the tooltip. It is possible they didn't find the colors contrasting enough or they might have used it to check each country's name. The results of the V3.1 tooltip also show the users had a little difficulty with it, but it was the second most useful tooltip. They also could have answered the question without the use of the tooltip as they just needed to look for the highest point and the highest column, yet the tooltip could aid to be sure of the correct result. All users took advantage of this tooltip. The heatmap's tooltip, V4.1, had the average lowest complexity evaluation and a good effectiveness evaluation. 17% of Non-Experient users answered they didn't use the tooltip, while 10% of Experient users responded the same. For the tooltip in the pie chart, V4.2, the complexity was a little higher than V4.1. Still, the average effectiveness for Experient users was interesting. They rated this tooltip as the least effective. As there were only 3 categories in the pie chart and it was possible to have a clear visualization of the proportions, it makes sense the tooltip wasn't much needed for the tasks for more experienced users. For Non-Experient users, it had almost the same average effectiveness as the other tooltips. 21% of Non-Experient users answered they didn't use the tooltip, while 14% of Experient users responded the same (Figure 4.37 and Figure 4.38).

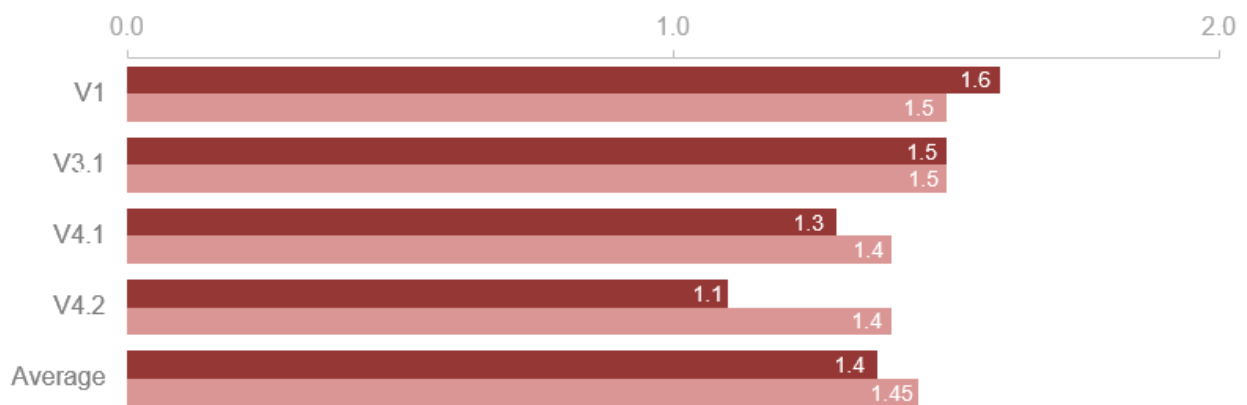


Figure 4.37 – Tooltip average effectiveness evaluation

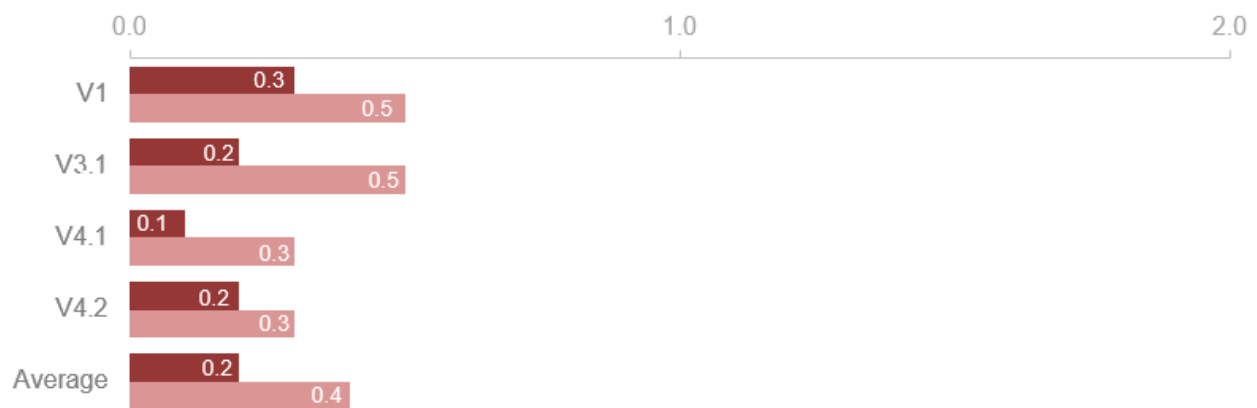


Figure 4.38 – Tooltip average complexity evaluation

Other elements and charts

The bubble chart (V2) was the element with the highest average complexity evaluation from all interactive options for both groups. It makes sense as this visualization was also considered complex, probably mostly due to this chart. On the other hand, as it was mandatory to complete the tasks using the chart, the effectiveness evaluation was high. Moreover, the tasks could have been answered with the assistance of the tooltip (slope chart). The tooltip was considered less effective than the bubble chart. Non-Experient users found both the tooltip and the bubble chart significantly more complex than the Experient users.

The bar and line chart in V1 had almost the maximum average effectiveness score. All other chart elements, as heatmap, bar chart, pie chart, data card, choropleth, had a high effectiveness rating as well. Still regarding effectiveness, the data card and the waffle chart had the lowest scores, but were still in the high effectiveness interval. The data card was mandatory to answer one of the questions, but some users used the wrong chart to respond, so this may be a reason why its score was lower, especially for Non-Experient users that got this answer wrong more often. Only 5% of Experient users said they didn't use the Data Card and 20% of Non-Experient users had the same answer.

Regarding the effectiveness, the zoom in V1 was among the least effective interactive elements and indeed there was no obligation to use it to answer the questions and some users reported difficulties using it. Indeed, 45% of Experient and Non-Experient users did not use the tool. The complexity varied a little and after the bubble chart, the waffle chart and the heatmap were the most complex, but still in the low complexity interval. A highlight has to be made to the waffle chart. Non-Experient users seem to have found this visual significantly complex, followed by the heatmap. Experient users considered those elements as complex as any other. For Experient users, the pie chart, the bar chart, and the data card were very easy to interpret (Figure 4.39 and Figure 4.40).

Components and charts with the highest and lowest average evaluation can be seen on tables. Concerning the components, Experient and Non-Experient assessments were very similar – the text component was excluded from the analysis. For the charts, the assessments were also analogous, but the complexity evaluation values had significant differences (Table 4.14 and Table 4.15).

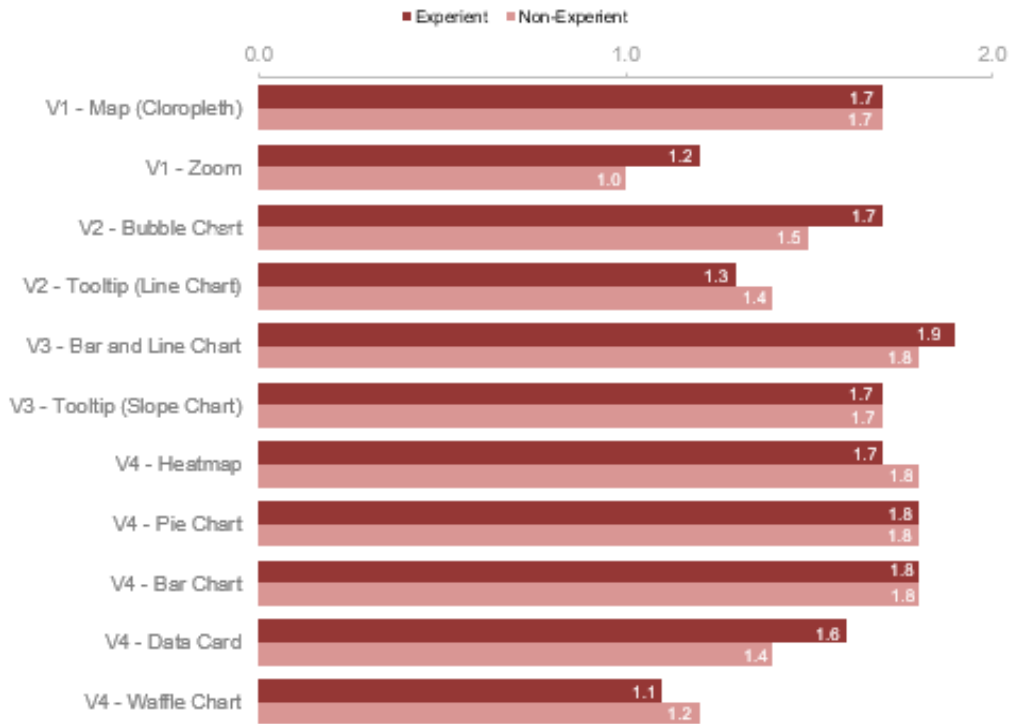


Figure 4.39 – Other elements average effectiveness evaluation

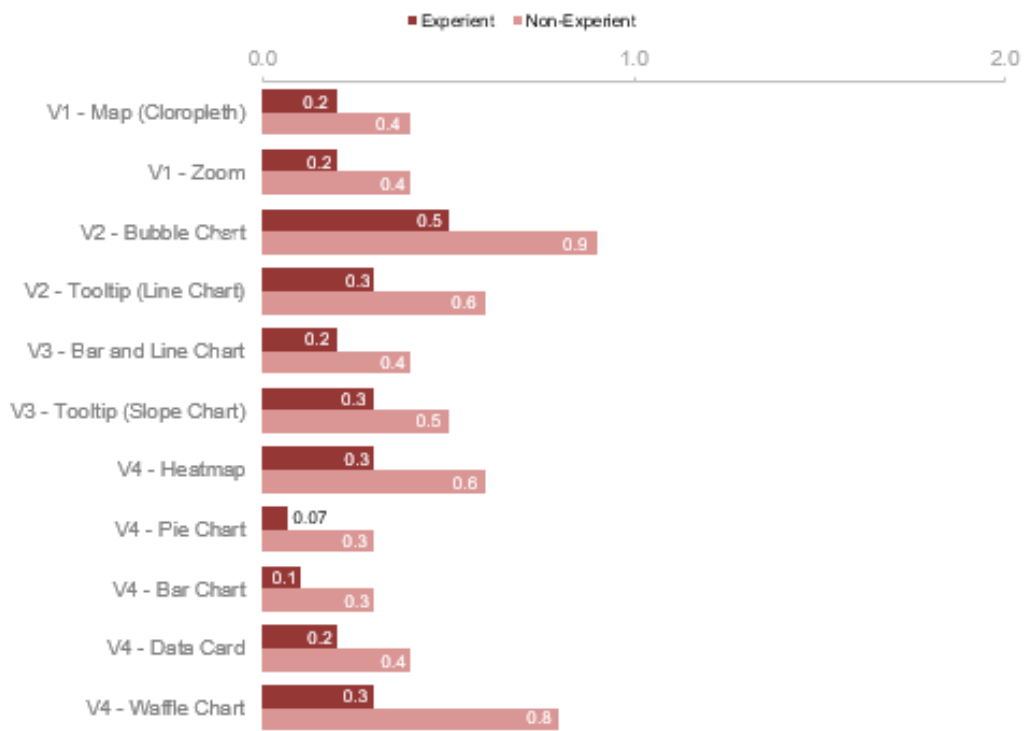


Figure 4.40 – Other elements average complexity evaluation

Table 4.14 – Results summary

Measure	Best		Worst	
	Experient	Not-Experient	Experient	Not-Experient
Complexity	Pie Chart (V4)	Pie Chart (V4) Bar Chart (V4)	Bubble Chart (V2)	Bubble Chart (V2)
Usefulness	Bar and Line Chart (V3)	Bar and Line Chart (V3) Pie Chart (V4) Bar Chart (V4)	Waffle Chart (V4)	Waffle Chart (V4)

Measure	Best		Worst	
	Experient	Not-Experient	Experient	Not-Experient
Complexity	Slider Filter	Filter	Animation	Animation
Effectiveness	Slider Filter	Slider Filter	Animation	Zoom

Table 4.15 – Charts complexity evaluation summary

Visualization	Charts Complexity			
	Highest		Lowest	
	Experient	Not-Experient	Experient	Not-Experient
V1	Cloropleth 0.2	Cloropleth 1.4		
V2	Bubble Chart 0.5	Bubble Chart 0.9	Line Chart 0.3	Line Chart 0.6
V3	Slope Chart 0.3	Slope Chart 0.5	Bar and Line Chart 0.2	Bar and Line Chart 0.4
V4	Waffle Chart and Heatmap 0.3	Waffle Chart 0.8	Pie Chart 0.08	Pie and Bar Chart 0.3

Comments - Survey and Interview

The last question in the survey was regarding any comments the user wanted to offer to improve the project. There was a total of 35 comments and 10 users also were available to discuss their feelings on the prototype and suggest improvements. The comments were split to keep 1 idea per line in Table 4.16.

Table 4.16 – User’s suggestions

Suggestion	Experient	Non-Experient	Viz
Highlight countries with max and min lendings each year	0	1	V1
Do not rely only in colors in V1: Use datacard when clicking a country	0	1	V1
V1 with a "more colorful" option	0	1	V1
Confusion in V1 tooltip (%GT)	1	2	V1
Option to use full screen	1	0	V1
Issues with the Zoom interaction	1	0	V1
Increase the animation time for each year	0	1	V1
Try another option for V2	0	1	V2
Highlight the animation	1	0	V2
Do not rely only in colors in V2: Use small labels next to bubbles	1	2	V2
Issue when clicking the bubbles	2	0	V2
Use exact values	1	1	V2
Bubble colors	1	0	V2
Draw a 45° line	1	0	V2
Allow to select more than 1 bubble	1	0	V2
In V2, the animation axis may be confused as the X axis	1	0	V2
Too many visuals in V4	3	1	V4
Interaction with Data Card and Column Chart in V4 should be easier to figure out	0	1	V4
Waffle Chart: relocate, use as tooltip or text	1	0	V4
Colorblind friendly	1	1	Prototype
Enhance design coherence: Always keep the same position for the same element, especially texts	1	0	Prototype
Too much information in the prototype/Use less visualization types	1	0	Prototype
Highlight or indicate in the text all buttons/interactions	1	1	Prototype
Use of bar race to complement V1 and V2	1	0	Prototype
Use less texts	1	1	Prototype
Create a button in all pages that lead to the Intro	1	0	Prototype
Use collapsed texts to increase charts' space	1	0	Prototype
Organize elements according the use (eg. First I select the filter and then I look at the chart)	0	1	Prototype
Use a gamification approach	1	0	Prototype
Beautiful / No changes / Very good / Good use of elements	5	7	Prototype
Full of insights	1	1	Prototype
Complex for Non-Experient users	0	2	Prototype

The issue that was raised the most was regarding the number and types of visualizations in V4. Indeed, the visualization was created to evaluate how the users would feel about this approach. In the same visualization, one user asked to be clearer regarding the data card interaction, which was also a tentative to evaluate if users would find this interaction easily. One user also commented about the use

of the waffle chart. The individual wrote that as there was no interactive filtering and the information was quite simple, it might be better to use it in another place and as a text, for example. Yet, V4 was the visualization that was voted Most Preferred by most Experienced and Non-Experienced users.

The main consideration in V1 was regarding the colors and to use another element to visualize the information when clicking a country. Another important consideration was the difficulty of users to understand the tooltip, which directly impacts the understanding of the whole visual. One user reported issues when using the zoom element and considering that few people tried to use it, it could be a good idea to remove this feature. One user suggested the option to use full screen and to make the animation slower.

Regarding V2, color was also an important topic. The idea was to divide the regions based on which entity lent more money, so different hues of blue and red were used. 3 users suggested adding a small label next to each bubble to facilitate the identification of regions. Another important comment was regarding the position of the play axis and how it was presented. Due to some Power BI limitations, those improvements will not be possible to be integrated into the prototype. A few users also asked to show the exact amount of lending, but this precise amount was not the intent for the visualization. A useful suggested improvement was the use of a 45-degree line to facilitate analysis.

Users also made valuable suggestions to improve the prototype as a whole, such as the use of collapsed texts, highlight or indicate in the text all the interactive elements, and how to enhance design coherence. Some users pointed out the need for a color blind friendly approach. Indeed, the color theme was selected using color blind support tools. Other recommendations, such as using a label in V2 were also considered by users. A few users highlighted that there was too much information or too many visualization types. This is a prototype developed to an academic work that tries to understand how users would engage and interpret different visualization idioms and elements, thus, this was the main reason for using many different approaches. In a real case scenario, the audience's expertise, needs, and expectations would have been considered before even starting the work development. On the other hand, many users approved the prototype as it was, and enjoyed the insights it provided.

Finally, it is important to highlight that due to software and project scope limitations not all improvements will be implemented.

4.3. PROTOTYPE IMPROVEMENTS

After considering the users' survey results, the prototype was improved. Regarding the prototype as a whole, the layout in V1 and V3 was updated to have a more cohesive layout. The use of collapsed texts was included for V1, V2, and V3.

In V1, the color palette used in the choropleth map was changed to more contrasting divergent colors, the Zoom interaction was removed, the animation time was increased and the information on the tooltip was simplified. Also, there was a reduction in the text explaining the visualization. As there was a

change in the color schema in the map, countries with maximum and minimum lending are now easier to distinguish, as one user pointed out. Instead of the option to use full screen, it was opted to take advantage of collapsed texts, allowing to have bigger visualizations.

Regarding V2, a very useful suggestion was to add a 45° line to facilitate the understanding of which entity was lending more money to each region. The play axis was highlighted to differentiate it from the X-axis and call attention to the feature. Small labels were also added next to the bubbles and instructions for interacting with the bubbles were added. There were no color changes as the labels were included and the color hue has a meaning in the visualization context. Also, the average lines for each axis were removed. The use of exact values was not the goal for this visualization, so this suggestion was not taken into consideration.

The use of different play axis in V1 and V2 is because Power BI does not support its own play axis in the standard map chart, so a different visual had to be imported to create the animation. This new play axis has a complex behavior with the standard bubble chart; therefore, the chart's animation setting was configured. The changes in V3 were only to maintain the layout coherence, and the collapsed text was added.

In V4, most of the issues were regarding the number of visualizations on the page. This was made on purpose to evaluate the user's reaction. Thus, the visualizations remained the same, except for the waffle chart. This was removed due to the complexity evaluation results from the Non-Experient group and because a user suggested replacing it with plain text. The interaction with the bar chart was highlighted with a note next to the chart. The layout remained the same and different from the others as the purpose of the visualization was different, focusing on a deep dive into the COVID-19 situation specifically and not general lending aspects.

5. DISCUSSION

This section focusses on the project results' critical assessment and builds a parallel with related studies. The motivation for this study was to democratize open data through the adoption of data visualization best practices and building visualizations that suit different types of audiences, as well to understanding how the visualization literacy level – that comprehends data and information literacy - can impact comprehension and information retaining. The understanding of this subject can be very beneficial to citizens and entities, enhancing their knowledge and allowing users to take advantage of the information.

Thus, this work's goals were to understand how groups with different data visualization literacy levels (Experient and Non-Experient users) discover interactivity in visualizations and which techniques are better suitable to each group. The approach was to create a prototype with different interactive visualizations and apply different interactive and visualizations techniques, using open data from The World Bank. The prototype was created based on narrative visualization (interactive slideshow) and storytelling techniques. The software Microsoft Power BI was chosen to develop the prototype due to its easy accessibility, ability to create interactive visualization, and increasing popularity. The prototype was evaluated by 94 users that were divided into 2 groups based on specific criteria regarding their assessed literacy skills. The prototype evaluation was made through a methodology created to assess the response from different groups based on qualitative and quantitative measures and based on metrics established by Zhu (2007) - accuracy, effectiveness, and utility. To test for statistically significant differences an ANOVA single factor test was used. Hence, this work contributed with a methodology to evaluate a prototype and offers an alternative methodology, with the use of open data and Microsoft Power BI, differing from previous correlated studies.

Regarding the results, the measures that had statistically significant differences were the comprehension (efficiency), complexity (utility), and accuracy. Therefore, all 3 principles for an effective visualization could be improved to reduce the gap between users with different data visualization levels. Also, users were asked regarding the effectiveness of each visualization. This assessment does not fully comply with the results obtained using with Zhu's metrics of effectiveness. Thus, it would be interesting to further analyse what is the concept of effectiveness to users. In addition, the results confirm that users with higher level of data and visualization literacy can take more advantage of visualizations and its interactive compounds, enhancing the effectiveness of the visualization. Plus, the use of interactivity possibly helped to leverage the extracted information, according to the results for this measure.

A notable result was that V2 (bubble chart) had the worst results for all measures for both groups. The users found the visualization complex and took more time to answer the question, besides having the worst accuracy rate. This contributed to V2 being the least preferred visualization and with the lowest engagement rate. However, users found the visualization almost as useful as the others. The suggested improvements made by the users, as adding a 45-degree line, probably can facilitate the visualizations' comprehension and understanding. Still, the use of bubble charts should be accompanied with clear instructions and features and should be avoided from visualizations aiming a broader audience.

V1 (choropleth map) had a high usefulness evaluation and was the visualization where Experienced users completed the tasks faster. This visualization had a better acceptance among Experienced users, and concerning user preferences, it had a similar ranking for the 2 groups. The use of more contrasting colors was suggested by users from both groups, so this change can positively impact the comprehension for all users. Maps can be a good solution to expose geographical data and users seemed to have good results with the chart and the interactive tools.

V3 (bar and line chart) had the lowest complexity rate, thus making sense that it was the visualization with better accuracy for both groups. The completion time in this visualization for Non-Experienced users was the highest though. V3 was also well rated for usefulness and effectiveness, along with V4 (multiple visualizations). V4 although being approved by most users, also had an increased complexity level for Non-Experienced users and the heatmap, even though was used correctly by this group, also had a complexity level that indicates this idiom should be carefully planned in visualizations. Having been said that, another remark must be made to V4. This visualization was created to represent a dashboard, with more detail regarding one certain topic. Although some users commented that this page had too much information, it was voted as the most preferred visual for both groups, as well, as the most engaging one. It also was highlighted for its usefulness and effectiveness for both groups. Plus, the accuracy rating for the tasks was high – except for the question where an interactivity was proposedly hidden – another evidence that higher levels of literacy can impact users' experience. It is possible that, along with the visualization format, the content of the visualization was more relatable to the audience, thus the good ratings. Users from both groups have voted V4 as the most preferred visualization and V3 was a close second for the Non-Experienced group. This result is coherent to the engagement rate, where V3 also had the best result – tied with V3 for Experienced users.

In summary, concerning the visualizations' idioms, both groups had similar results and they are coherent to the results shown previously. V2 was ranked the most complex and the visualizations in V3 and V4 the most useful and least complex. The waffle chart was the least useful visualization type for both groups and was assessed as having a medium complexity by Non-Experienced users, so it is possible that users were uncomfortable with it as it is an unusual idiom. In addition, there were comments questioning the need of using it instead of a text or data card, hence, the results. Regarding Experienced users, all idioms had a similar assessment within the group. The tasks dependent on the bubble chart had the worst accuracy for both groups, what is aligned with the fact it was ranked as the most complex idiom. The pie and bar chart were the 2 idioms with better results for both groups. Since they are very usual visualizations, it makes sense that they were easily understood, especially by the Experienced group. Even though they are simple charts, they are still very useful and offer excellent results to facilitate users' interpretation and should be preferred when designing for broader audiences.

Considering only interactive elements, and excluding the visualizations, Experienced and non-Experienced users had a close average effectiveness assessment for all items, reaching a total of 1.5 in 2, considered a high usefulness. The complexity assessment was a little different for both groups, however. Experienced users classified elements' complexity with an average of 0.23, while Non-Experienced users presented an average of 0.5. According to the previously defined criteria, the interactive elements had an average low

complexity and high effectiveness for both groups, but close to the medium border for the Non-Experient group. For Experient users, the slider and filter elements were both rated as the most useful and least complex. Similarly, Non-Experient users found slider and filter elements the most useful, but only the filter as the least complex. Both groups responded well to those interaction and the results show that the use of interactive elements is suitable to all audiences and when explained properly users can easily take advantage of it. Once again, the difference in literacy levels lead to different results for the complexity measure. The use of interactive elements can improve the understanding and presentation of the information, allowing the user to explore and to delve into each subject and explore different abstraction levels. Depending on how the filter is designed and placed in the layout, as well as the number of choices, Non-Experient users showed slightly different complexity rates, as it could be seen for the different filters used in V1 and V4.

Both groups found the animation element complex and the Experiment users found it also the least effective tool. This is interesting as this approach is a well-known alternative to display changes over time. The Non-Experient users ranked the zoom element as the least effective. Indeed, plenty of users reported the did not take advantage of those elements and pointed out some difficulties while using it.

The previous results, regarding all metrics to evaluate the prototype, shown that the tool Microsoft Power BI can provide an environment to create interactive visualizations to the general audience, providing tools and functionalities that allow groups with different visualization literacy levels understand the visualizations, interact with them and extract information. Yet, the prototype was created taking in consideration data visualization rules of thumb and best practices, as well, as the interactive slideshow schema for narrative visualizations. Some suggestions based on Blackscheck et al. (2018), Boy et al. (2016), Munzner (2015) and Figueiras (2015) approaches to elaborate interactive techniques and more discoverable interactions were used. Probably those techniques impacted the perceived usefulness, effectiveness, and complexity of the prototype in general.

Comparing the results from this experiment with others in the literature, it is possible to find some similarities and differences. This project followed the existing work on the subject regarding the evaluation assessment, using both quantitative and qualitative measures. The results, however, can differ in a few points from the literature. This work found differences between how Experient and Non-Experient users perceive interactive tools. The work by Concannon et al. (2018) found statically significant differences between groups with different computer literacy levels regarding to tasks' completion time, what was not true to this project. A common ground for Concannon et al. (2018) work and this experiment was that users with higher levels of literacy obtained more correct answers. Also, in both works, the different groups found the visualizations useful. The tests made by Oghbaie et al. (2016) and Rouse et al. (2017) found no statistically significant differences in groups for speed, but the accuracy measure shown statistically significance. Those results are alike with the ones concluded in this project, as there was no difference for task time completion while there was difference for accuracy. Also, in both projects suggest that Experient users were able to extract more information.

Blascheck et al. (2019) conducted an experiment with different types of users divided into groups, where the authors did not find differences in how groups perceived interactivity in visualizations. The

current project found differences in user's qualitative assessment of complexity and extracted information regarding the interactive visualizations. On the other hand, the finding in this project also shown that both groups present similar ideas regarding interactive elements preferences and comprehension. Finally, when comparing this project with the work presented by Géryk (2015), where the use of animations led to fewer errors. In the current work experiment, 2 visualizations took advantage of animated methods. The choropleth map (V1) obtained good accuracy results, but the bubble chart (V3) shown a lower accuracy score and most users rated the visualization badly in all evaluations. Also, V3 and V4 did not have animation options and showed the best evaluation in almost all criteria, for both groups. Although V4 had no time related analysis, V3 included a time measure. Thus, this project shows that the use of animation must be carefully thought and do not guarantees high accuracy rates.

Concerning the use of SI cues, following the concepts brought Boy et al. (2016) work, the use of external objects, such as filters and sliders, were effective to help identifying the interactivity for both groups. Those elements had a high acceptance for the users and were also considered easy to use. The prototype in this work took advantage of texts to use SI cues, which seem to be effective as the users provided good evaluations for this feature and were able to find the interactions. Also, Boy et al. (2016) experiment confirmed the hypothesis that less participants discover interactivity without the cues. This conclusion agrees with the experiment made in this project, where in V4 an interactive action did not have any SI cues and most users – especially Non-Experient ones – were not able to discover the interactivity.

Finally, users clustered in the Experient group were considered individuals with visualization literacy skills, meaning they were able to use visualizations to translate questions into visual queries and extract information from graphical representations. As visualization literacy involves the concepts of data, information and digital literacy, the comparison between the results from groups with different literacy levels showed that this ability can improve user's performance and capacity to extract information. The use of interactivity is an approach to reduce the gap between groups, yet there's still more work to be done to understand how and what are the best practices to improve the quality of information extracted by the general audience. Therefore, projects as DATALIT that aim to develop data literacy skills, should be encouraged in social, academic, and business environments, as the gain society and the users can have when they are able to enhance their capability to understand data is valuable.

The use of more usual idioms, such as pie and bar charts, along with simple short texts and notes informing the possible interactions can increase all users understanding of the visualizations. Also, both groups seem to prefer the use of visualizations more focused into one specific subject they can easily relate, like a dashboard. The number of visualizations, however, must be controlled to avoid overwhelming the user. Another consideration is that the visualization developer should emphasis using only texts and data cards to represent general numbers, instead of using visualizations that can be complex to non-expert users and clutter the visualization.

6. CONCLUSIONS

This study intended to create interactive visualizations based on data visualization best practices, interaction techniques and suggested interaction approaches to evaluate how users with different literacy levels would interact, comprehend, and engage with visualizations, aiming to create effective visualizations with open data. Users had to respond a survey with their background details, questions to evaluate their ability to retrieve information from the visualizations and their opinion and feelings about them. Using ANOVA single factor test, it was possible to identify 3 metrics that had statistically significant differences between both groups: accuracy, complexity and extracted information.

Concerning visualizations' idioms, the bubble chart was considered complex for both groups, the accuracy for questions based on this chart was the lowest and users selected this visualization as their least preferred. All other visualizations had a good acceptance among users, especially the bar, line and pie charts., that are very common idioms. The waffle chart was not well rated for the users and some of them commented there was no need to use it. The evaluation of interactive elements was positive for both groups, even though the Non-Experient group found it a little more complicate. Both groups found it pleasant to work with filters and sliders. Tooltips had a good acceptance too. Animations were considered complicated by both groups and some users even did not use this interactive tool. There was one interactivity that was not explained in the text, most Experient users could find and take advantage of it, but Non-Experient users had more difficult to find it. Based on comments and other results, the use of explanatory texts, contextualizing the visualizations and interactive options is when dealing with very different audiences. However, the texts and types of visualizations should be the simplest as possible. Users approved the use of more than one idiom in the same visualization, yet it is preferable that the chosen idioms are common, as data cards and pie charts. Thus, companies and organizations can use the results to design more accessible visualizations with open data to the general audience.

Finally, the metrics that showed statistically significant differences between both groups stress the importance of developing data literacy skills. Experient users demonstrated higher performance regarding accuracy, comprehension, and complexity. Each measure complements each other, so if the user finds the visualization hard to read and understand, the chance of getting inaccurate answers from it or extracting less value is higher. Therefore, projects as DATALIT and the use of interactivity are of importance to democratize data and allow the general audience to extract better information from it.

It is important to highlight some limitations in this work. As this experiment was conducted during the COVID-19 pandemic, it was not possible to create a controlled environment and observe all user during the process of answering the survey. Also, users had to change screens between the visualizations and the survey, what could impact their performance. The number of experimented idioms and interactions was also restricted, but considering the available time and users' availability, it would not be feasible to have more visualizations to test. As for future works, a gamification approach could be used for the questionnaires and opt for more relatable topics could improve users' engagement. Another suggestion is to include a deeper explanation of the metrics and how they relate to an effective visualization before users evaluate each metric.

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ANNEX A – SURVEY

Part 1 - Personal background

What's your age group?

18 - 20

21 - 30

31 - 40

41 - 50

51 - 60

61 or older

What's your education level?

High School

Technical Certificate

Bachelor's Degree

Master's Degree or Postgraduate

Doctorate

What is your area of specialization?

What is your current occupation?

Have you ever used data analysis or visualization in your work?

- Yes, data analysis
 - Yes, data visualization
 - Yes, data analysis and visualization
 - No.
-

Which of the visualization types below do you know and can interpret? You can select more than one type of visualization.

- | | | | |
|--------------------------|-------------------|--------------------------|-------------------|
| <input type="checkbox"/> | Pie Chart | <input type="checkbox"/> | Area Chart |
| <input type="checkbox"/> | Bar Chart | <input type="checkbox"/> | Bubble Chart |
| <input type="checkbox"/> | Stacked Bar Chart | <input type="checkbox"/> | Heatmap |
| <input type="checkbox"/> | Tables | <input type="checkbox"/> | Scatter Plot |
| <input type="checkbox"/> | Matrixes | <input type="checkbox"/> | Tree maps |
| <input type="checkbox"/> | Histogram | <input type="checkbox"/> | Map or Choropleth |
| <input type="checkbox"/> | Line Chart | <input type="checkbox"/> | Boxplot |
-

Take a look at the visualizations below:

How do you feel after evaluating the images above?

- I am familiar with all the visualizations and can interpret them with little or no additional information.
 - I recognize some of the visualizations and I believe I am able to interpret those that I do not know with some additional information.
 - I recognize some of the visualizations and I believe I am NOT able to interpret the ones I don't know even with some additional information.
 - I don't recognize any visualization.
-

When you read articles from newspapers or websites, do you prefer the information to be accompanied by graphic visualizations?

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

How easy do you find to understand these visualizations?

- Extremely easy
- Somewhat easy
- Neither easy nor difficult
- Somewhat difficult
- Extremely difficult

Can you answer questions based on the information obtained through visualizations?

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

Do you know what an outlier is and methods of identifying it through visualizations?

- Yes
- I know what it is but I can't identify it
- No

Can you find correlations through visualizations?

- Yes
 - No
-

Part 2 - Quantitative assessment

Visualization 1 - Map

In 2015, China received more lendings during the year than Brazil, and less investments than India.

- True
 - China only received more investments than Brazil
 - China only received less investment than India
 - False
 - It isn't possible to answer / I don't know
-

In South America, when considering all years, Brazil is the country that receives more lending.

- True
 - False
 - It isn't possible to answer / I don't know
-

Between 1990 and 2020, which country received the most investments in the Health sector?

- Italy
 - Australia
 - India
 - Argelia
-

Visualization 2 - Bubble Chart

What does it mean when a point is above the horizontal dashed line?

- The lendings in the given year is above the average of loans granted by IBRD, considering all years of the selected period
 - The lendings in the given year is above the average of loans granted by IDA, considering all years of the selected period
 - The lendings in the given year is below the average of loans granted by IBRD, considering all years of the selected period
 - The lendings in the given year is below the average of loans granted by IDA, considering all years of the selected period
-

From 2015 to 2020, which of these regions below received more lendings from IBRD than from IDA?
You can select more than 1 option.

- Latin American and Caribbean
 - Africa West
 - South Asia
 - Europe and Central Asia
-

The sentence "Between 2014 and 2019, in each year, Africa West received more lendings from IDA than South Asia" is:

- True
 - False
 - It isn't possible to answer / I don't know
-

Visualization 3 - Line and Bar Chart

What was the year with the most number of approved projects and what was the year with the higher amount of approved lendings?

- Projects: 2020 ; Lendings: 2010
 - Projects: 2020 ; Lendings: 2020
 - Projects: 2014 ; Lendings: 2010
 - Projects: 2010 ; Lendings: 2020
-

In 2014, what was the sector that had the highest increase in the amount of approved lendings?

- Water
 - Social Protection
 - Education
 - Financial Sector
-

Based on the information shown in the visualization, do you agree with the statement: The international scenario is a variable that can directly influence approved projects by the World Bank.

- Yes
 - No
 - It isn't possible to answer / I don't know
-

Visualization 4 - Different visualizations

In which month there were more approved projects directly related to COVID-19?

- March
- April
- May
- June

How many countries in Latin America and Caribbean have received lendings for projects directly related to COVID-19?

- 13
 - 20
 - 16
 - It isn't possible to answer / I don't know
-

Which region has the second largest number of approved Social Protection projects directly related to COVID-19?

- South Asia
 - Latin America and Caribbean
 - Africa West
 - East Asia and Pacific
-

IBRD sponsored more IT and Communications and Social Protection projects, together, than IDA.

- True
 - False
 - It isn't possible to answer / I don't know
-

Part 3 - Qualitative assessment

Visualization 1 – Map

When answering the previous questions, do you agree the first visualization was:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Effective	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Engaging	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Complex	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their usefulness to answer questions and interact. You can see the description of each element in the images in the beginning of this page.

	Effectiveness			
	Low	Medium	High	Not used
Map (Choropleth)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Slider (choose years)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Zoom	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Filter (choose sectors)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Animation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their complexity to interact. You can see the description of each element in the images in the beginning of this page.

	Complexity			
	Low	Medium	High	Not used
Map (Choropleth)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Slider (choose years)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Zoom	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Filter (choose sector)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Animation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Visualization 2 - Bubble Chart

When answering the previous questions, do you agree the second visualization was:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Effective	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Engaging	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Complex	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their usefulness to answer questions and interact. You can see the description of each element in the images in the beginning of this page.

	Effectiveness			
	Low	Medium	High	Not used
Bubble Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Slider (choose years)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip (Line chart)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Animation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their complexity to interact. You can see the description of each element in the images in the beginning of this page.

	Complexity			
	Low	Medium	High	Not used
Bubble Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Slider (choose years)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip (Line chart)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Animation	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Visualization 3 - Bar and Line Chart

When answering the previous questions, do you agree the third visualization was:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Effective	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Engaging	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Complex	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their usefulness to answer questions and interact. You can see the description of each element in the images in the beginning of this page.

	Effectiveness			
	Low	Medium	High	Not used
Bar and Line Chart (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip 1 (Line chart) (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip 2 (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Q66 Classify the following components according to their complexity to interact. You can see the description of each element in the images in the beginning of this page.

	Complexity			
	Low	Medium	High	Not used
Bar and Line Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip 1 (Line chart)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltip 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Visualization 4 - Multiple visualizations

When answering the previous questions, do you agree the forth visualization was:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Effective	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Engaging	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Complex	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Classify the following components according to their usefulness to answer questions and interact. You can see the description of each element in the images in the beginning of this page.

	Efectiveness			
	Low	Medium	High	Not used
Heatmap (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Pie Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bar Chart (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Datacard (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Waffle Chart (13)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Filter (choose sectors) (14)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltips (15)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



Q74 Classify the following components according to their complexity to interact. You can see the description of each element in the images in the beginning of this page.

	Complexity			
	Low	Medium	High	Not used
Heatmap (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Pie Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Bar Chart (12)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Datacard (11)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Waffle Chart (13)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Filter (choose sectors) (14)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Text	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Tooltips (15)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

How would you rate the level of understanding of the visualisations?

- Poor. I was not able to understand the visualisations.
 - Below Average. I was able to understand the visualisations after some time.
 - Average. I was able to understand the visualisations but not withdraw an analysis.
 - Above Average. I was able to understand the visualisations and withdraw an analysis of the context after a few minutes.
 - Excellent. I was able to understand the visualisations and withdraw an analysis of the context right away.
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How would you rate the information analysis and extracted messages/insights of the visualizations?

- Poor. The analysis did not provide me with any insights.
 - Below Average. The analysis provided me with possible insights – more information is needed.
 - Average. The analysis provided me with expected insights.
 - Above Average. The analysis provided me with somewhat interesting insights.
 - Excellent. The analysis provided me with surprising insights.
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Regarding the prototype as whole, do you agree it was:

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Useful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Effective	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Engaging	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Complex	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



Classify the visualizations according to your preference. Mark only one visualization for each column.

	Most preferred	Prefer a lot	Prefer slightly	Least preferred (15)
Visualization 1 - Map	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Visualization 2 - Bubble Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Visualization 3 - Bar and Line Chart	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Visualization 4 - Multiple visualizations	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Do you have any suggestions for improving the prototype?

