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Abstract

The study presented in this paper investigates how two groups, with different literacies, perceive interactive visualizations by using statistical tests. A prototype with interactive visualizations created with Microsoft Power BI has been used. Validation was made with quantitative and qualitative metrics tested with ANOVA single factor. Three of the variables showed statistically significant differences between groups: accuracy, complexity, and comprehension. This highlights the importance of data literacy in comprehending visualizations, leading to a gap between both groups. The line, pie and bar chart were considered the best visualizations for both groups, and the worst was the bubble chart. Regarding the interactive component, the filter and the slider had a good evaluation among both groups. Using this study, organizations will be able to create appropriate visualizations for different audiences.

Keywords: Data Visualization; Data Literacy; Interactivity

1. INTRODUCTION

The open data movement has increased providing reliable free of charge information for public use and enhancing transparency and relations between governments and citizens, boosting development and innovation, and improving decision-making. Open data use is low and limited to researchers, private sector, and technical users, yet it could be of worth to non-technical users, as the everyday citizen. Data availability does not guarantee usage and engagement among the public because of data organization and presentation, and user's lack of data literacy skills. Usually, data is provided in raw formats, without metadata or context, or considering that groups use data differently and the general audience does not have the means or skills to access, explore and understand data (Chua et al., 2020; Gebre & Morales, 2020; Blascheck et al., 2017). An approach to make open data more accessible is via web-based interactive visualizations that enhance comprehension and communication, attract users, and are a tool for data democratization. User's ability and confidence in understanding visualization is crucial to be assessed through the user's literacy level. However, not all citizens are literate or are aware of this concept (Boy et al., 2015; Borne et al., 2015; Rodrigues et al., 2020; Lee et al., 2020; Blascheck et al., 2019).

This study investigates how groups with different literacies discover interactivity, through the creation of a prototype with interactive visualizations and using ANOVA single factor test to find statistically significant differences. The prototype was developed with Microsoft Power BI, using data visualization best practices, interactivity, and suggested interaction. The results are useful to improve communication with different audiences and highlight the importance of data literacy and understanding how different levels influence comprehension and retained information.

2. RELATED WORK

2.1. Data Literacy

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. (Bhargava et al, 2015; Carmi et al., 2020; Raffaghelli, 2020; Pothier & Condon, 2019).

Some authors (Bhargava et al., 2015; Calzada Prado & Marzal, 2013) define data literacy as a central component of information literacy. According to the Association of College and Research Libraries (2000), 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. In the same way as data literacy, it is also imperative to enable citizens to actively participate in their community affairs and be more involved (Batool & Webber, 2019). A study by Lee et al. (2020) concluded that the higher the information literacy, the lower the information overload is perceived, and the lower the information overload a person perceives, the higher usefulness the user realizes.

Similarly, visualization literacy assesses many types of literacy, including data and information literacy. (Rodrigues et al., 2020; Lee et al., 2020). Literacy assessment is useful for understanding audience's capacity of reading visualizations and evaluate acquired knowledge (Boy et al., 2015). A study conducted by Blascheck et al. (2017) concluded that low levels of visualization literacy can influence the preferred type of visualization and experiments made by Boy et al. (2016) showed that visualization literacy levels reflected on how users discover and engage with interactivity. Low literacy levels users may have a minor propensity to interact and discover visualizations, however, the literacy problem seems to be solved when questions and charts are highly congruent.

2.2. Interactivity

A solution to make open data more accessible is with interactive visualizations, using it as an instrument to aid visual exploration and insight generation with less need of expertise (Blacksheck et al., 2018; Boy et al., 2016). Interactivity has the purposes of make data more engaging or playful, and show it in manageable portions, reducing the complexity. Examples of interaction techniques are filtering, selecting, reconfigure, gamification, connect and collaboration (Figueiras, 2015).

2.3. Evaluation Metrics

Among the literature, there are different concepts of “effectiveness”, and the definitions are often incomplete. Effectiveness can be related to several subjects involving support on tasks, correctness, accuracy, and truth. The dataset, the defined tasks, and the questions asked to assess effectiveness are only a few factors that impact the evaluation. User’s expertise, memory, domain, 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 in which users move the mouse or the visualization latency (Zhu, 2007; Munzer, 2015).

Böschen et al. (2017) required numerical values as answers for tasks and collected qualitative 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. The study also computed task completion time and eye-tracking information. Abell & Churcher (2009) used the total time, number of times the interactivity was used, number of clicks and answer values to evaluate their experiment. Géryk (2015) evaluated users' accuracy, completion time, and subjective preferences and significant effects were measured with ANOVA. Similarly, Concannon et al. (2019) evaluated the effectiveness by measuring task completion time and answer accuracy, using ANOVA to test for significance, and participants completed a questionnaire regarding their knowledge on the subject domain, thoughts on the visuals and computer literacy based on a Likert scale.

3. DATA AND METHODS

3.1. Data

The public dataset is provided by The World Bank (TWB) via its Data Catalog website: <https://datacatalog.worldbank.org/dataset/world-bank-projects-operations>. The dataset concerns to TWB Projects & Operations regarding lending projects worldwide. It was released in 2010 and is constantly updated. The version used was from January 2021 and the period of analysis was between 1947 and 2020, included. There is no visualization available regarding this data on the 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 comprehend TWB work and how it is compatible with its missions.

3.2. Visualizations

The prototype consists of a foreword page and 4 different interactive visualizations (Table 1). The visualizations were developed considering color accessibility, narrative visualization, storytelling techniques, and the considerations from previous sections.

Component	Description
V1 Map	A choropleth map is used to create a spatial analysis to encode the lending to each country (quantitative), taking advantage of color hue and available geographical information (qualitative).
V2 BubbleChart	A bubble chart encoded 3 different attributes – the lending by each one of the 2 institutions (quantitative) and the supported regions (qualitative).
V3 Line andBar Chart	The charts show a trend over time of the total amount of approved projects (line) and thetotal amount of approved lending (bar)
V4 Multiple visualizations	The proposal was to elaborate a dashboard with different visualization types. A heatmapshows a time analysis comparing the number of COVID-19 related and others approved projects monthly. A waffle chart informs the percentage of approved projects related to COVID-19 initiatives. A bar chart shows the number of projects approved by region. A pie chart brings the rough distribution of the amount lent by each institution. A data cardshows the number of countries supported by initiatives.

Table 1 – Developed visualizations

3.3. Interactive components

Following the suggestions by Blacksheck et al. (2019) to scaffold complex interactions, avoid oscillation, keep spatial organization, and provide entry points, each visualization has a similar layout composed of a small text providing context to the page and covering different themes, so the user does not need to go back and forth to understand the information (Table 2). There are also suggested actions for the user in the text (Boy et al., 2016).

Component	Description
Filter	Available in V1 and V4, in different formats but for the same filtering option (project sector). In V1 there were more options to choose from and the user could search them through an entry point or using a bar slide and select by clicking the respective box. In V4,all options were visible, and the user could not search, and had to selected also by clickingthe respective box. Data was adjusted automatically.
Slider	Available in V1 and V2. In both cases it filtered the years to be analyzed. The user coulduse the entry points to select the year or use the slider. Data was adjusted automatically.
Play axis / Animation	Available in V1 and V2, allowing to show an animation of the changes in the data throughout the years. It was provided a play button to start the animation and invite users tointeract with the visualization, since inviting interaction is one of the suggestions by Blascheck et al. (2017).
Tooltips	Used in all visualizations in different contexts when the user passes the mouse on the interactive element. For the map, bar, line and pie chart and heatmap, it shows the attribute value. In the bubble chart, it reveals a line chart with the lending by each institution over the years, along with the region name. In V3, there are information buttons that show a tooltip with a slope chart indicating the difference in lending for different project sectors from one year to another.

Table 2 – Interactions used in the visualization

3.4. Experiment

After the development of the Microsoft Power BI prototype, 94 users completed an online survey that evaluated user's literacy level with open and multiple-choice questions. The questions regarding the prototype, asked users to perform tasks and respond to their feelings about the visualizations.

The evaluation was based on the concepts of effectiveness defined by Zhu (2007). The accuracy assessment was evaluated by 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 Zhu's concept.

To test for statically significant differences between groups, an ANOVA single factor test was conducted based on the mean values of each measure, either qualitative or from the Likert scale. This approach was applied by authors as Géryk (2015); Oghbaie et al. (2016) and Rouse et al. (2017).

4. Results and Discussion

4.1. Prototype

The first result of this study was the prototype. The visualizations are available on: <https://bit.ly/3fRioYI>, and on Figure 1 and Figure 2.

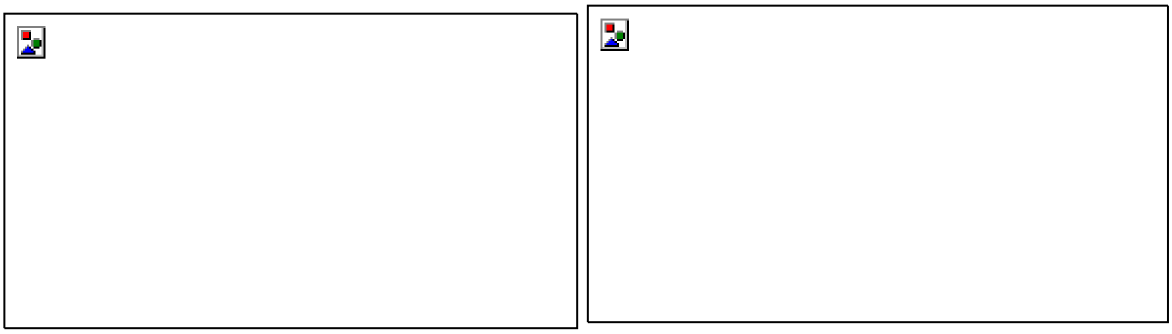

Figure 1 – Prototype V1 and V2

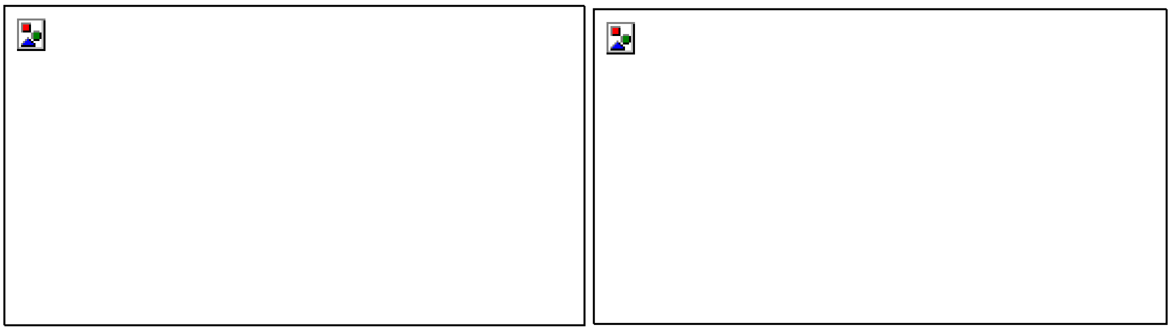

Figure 2 – Prototype V3 and V4

4.2. Metrics

94 individuals were evaluated, 42 classified as Experient users (higher literacy level) and 52 as Not-Experient (lower literacy level). The metrics were quantitative (accuracy and the completion time) and qualitative (extracted information, comprehension, usefulness, engagement, complexity, and effectiveness). The average of each metric for the groups were computed and classified into 4 categories. To test for significant statistic, an ANOVA single factor test was conducted. The metrics considered statistically significant and showed that there is difference between the results of groups were accuracy (p=0.00061), complexity (p=0.007289) and comprehension (p=0.00016). The other metrics did not show significant differences between groups (Table 3).

METRIC	EXPERIENT	NOT-EXPERIENT	ANOVA RESULT
Accuracy	88.5%	78.4%	F(3.9) = 12.579, p = 0.000616
Time (minutes)	20.5	28.0	F(3.9) = 0.846, p = 0.360062
Usefulness	3.8	3.7	F(3.9) = 0.687, p = 0.409077
Engagement	3.5	3.3	F(3.9) = 0.877, p = 0.3513
Complexity	1.9	2.6	F(3.9) = 7.531, p = 0.007289
Comprehension	3.5	2.9	F(3.9) = 15.501, p = 0.00016
Extracted Information	3.1	2.8	F(3.9) = 3.153, p = 0.079079
Effectiveness	3.8	3.6	F(3.9) = 1.131, p = 0.29017

Table 3 – Metrics results

All three principles for an effective visualization could be improved to reduce the gap between users with different data visualization levels. Users were asked regarding the effectiveness of each visualization and this assessment does not fully comply with the results obtained using Zhu's metrics. 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 literacy can take more advantage of visualizations and its interactive compounds, enhancing even more visualizations' effectiveness.

4.3. Visualizations

Concerning the visualizations' idioms, groups had analogous results, and regarding Experient users, all idioms had a similar assessment within the group. Users were asked about their overall visualization preference and the result is shown in Figure 3 and 4.

V2 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 use of bubble charts should be accompanied with clear instructions and features and should be avoided from visualizations aiming a broader audience.

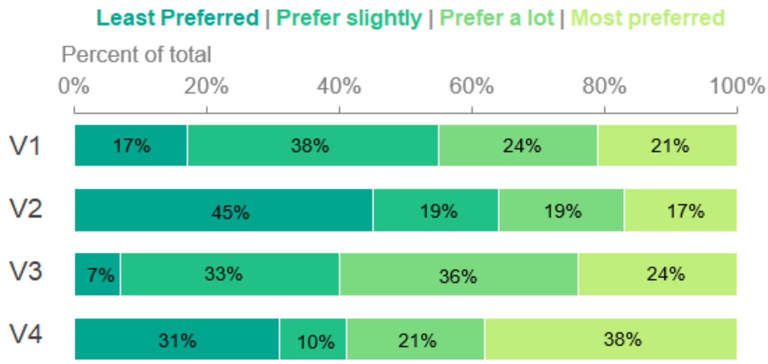

Figure 3 – Visualization Preference – Experient Group

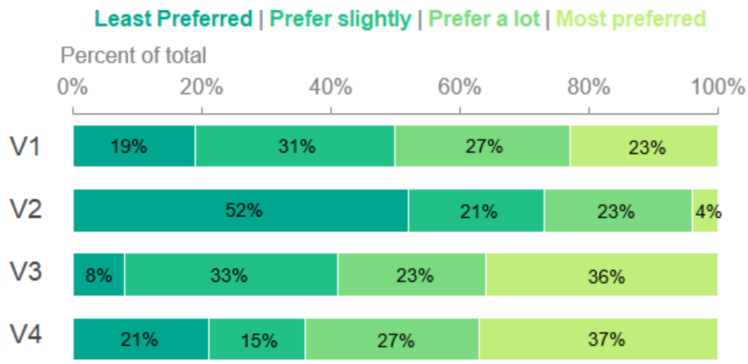

Figure 4 - Visualization Preference – Not-Experient Group

V3 had the lowest complexity rate, thus making sense that it was the visualization with best accuracy for both groups. The completion time in this visualization for Not-Experient users was the highest though. V3 was also well rated for usefulness and effectiveness, along with V4. V4 although being approved by most users, had an increased complexity level for Not-Experient users, and the heatmap, even though it was used correctly, also had a complexity level that indicates this idiom should be carefully planned. Another remark must be made to V4. This visualization was created to represent a dashboard, with more detail regarding a 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 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 engagement rate, where V3 also had the best result – tied with V3 for Experient users. V3 and V4 were ranked the most useful and least complex visualizations for both groups.

The pie and bar chart were the two idioms with better results for both groups. Since they are usual visualizations, it makes sense that they were easily understood, especially by the Experient 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. The waffle chart was the least useful visualization type for both groups and was assessed as having a medium complexity by Not-Experient 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, and the number of visualizations must be controlled to avoid overwhelming the user.

V1 had a high usefulness evaluation and was the visualization where Experient users completed the tasks faster. This visualization had a better acceptance among Experient users, and concerning user preferences, it had a similar ranking for the 2 groups. The use of more contrasting colours 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.

4.4. Interactive components

Considering only interactive elements, both groups had a close average effectiveness assessment for all items, considered as a high usefulness. The complexity assessment was a little different for both groups, however. Experient users classified elements' complexity with an average of 0.23, while Not-Experient 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 Not-Experient group. Concerning the use of SI cues, the use of external objects, were effective to help identifying the interactivity for both groups.

For Experient users, the slider and filter elements were rated as the most useful and least complex. Similarly, Not-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. Again, the difference in literacy levels lead to different results for the complexity measure. 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 and plenty of users reported not taking advantage of it, and other pointed difficulties using it.

4.5. Additional findings

As visualization literacy involves the concepts of data and information 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 is 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.

5. CONCLUSION

Using ANOVA single factor test, it was possible to identify three metrics that had statistically significant differences between both groups: accuracy, complexity, and comprehension. Those metrics stress the importance of developing data literacy skills. Experient users demonstrated higher performance in all criteria. Each measure complements each other, so if the user finds the visualization hard to read, the chance of getting inaccurate answers from it or extracting less value is higher. Therefore, projects as DATALIT are important to democratize data and allow the general audience to take advantage of it and the use of interactivity can aid to leverage the extracted information for groups with different literacy levels.

It is important to highlight some limitations in this work. 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 tests was also restricted considering time and users' availability. 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 other metrics and a deeper explanation of them, and how they relateto an effective visualization before users evaluate each metric.

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REFERENCES

Abell, W., Lee, J., Churcher, C., (2008). An evaluation of interactive stacked bar charts, *5th*

International Conference on Information Technology and Applications, pp. 147-151.

Association of College and Research Libraries, K. (2000). Information literacy competency standards for higher education, http://www.ala.org/acrl/standards/informationliteracycompetency (April 5th, 2021).

Baigelenov, A., & Parsons, P. (2018). Interactivity factors in visualization-based exploratory search. Conference on Human Factors in Computing Systems.

Batool, S. H., & Webber, S. (2019). Mapping the state of information literacy education in primary schools: The case of Pakistan. In Library and Information Science Research, pp. 123–131.

Bhargava, R., Deahl, E., Letouzé, E., Noonan, A., Sangokoya, D., & Shoup, N. (2015). Beyond Data Literacy: Reinventing Community Engagement and Empowerment in the Age of Data.

Blascheck, T., Vermeulen, L. M., Vermeulen, J., Perin, C., Willett, W., Ertl, T., & Carpendale, S. (2019). Exploration strategies for discovery of interactivity in visualizations. IEEE Transactions on Visualization and Computer Graphics, 25(2), pp. 1407–1420.

Börner, K., Maltese, A., Balliet, R. N., & Heimlich, J. (2016). Investigating aspects of data visualization literacy using 20 information visualizations and 273 science museum visitors. Information Visualization, 15(3), pp. 198–213.

Böschen, F., Strobel, E., Goos, S., Liebers, C., Rathje, A., & Scherp, A. (2017). Evaluation of the comprehensiveness of bar charts with and without stacking functionality using eye-tracking. CHIIR 2017 - Conference Human Information Interaction and Retrieval, pp. 337–340.

Boy, J., Detienne, F., & Fekete, J. D. (2015). Storytelling in information visualizations: Does it engage users to explore data? Conference on Human Factors in Computing Systems, pp. 1449–1458.

Boy, J., Eveillard, L., Detienne, F., Fekete. (2016). Suggested Interactivity : Seeking Perceived Affordances for Information Visualization.

Calzada Prado, J., & Marzal, M. A. (2013). Incorporating data literacy into information literacy programs: Core competencies and contents., Libri. 63(2), pp. 123–134.

Carmi, E., Yates, S. J., Lockley, E., & Pawluczuk, A. (2020). Data citizenship: Rethinking data literacy in the age of disinformation, misinformation, and malinformation. Internet Policy Review, pp. 1–22.

Chua, U. C., Santiago, K. L., Ona, I. B. M., Peña, R. M. N., Marasigan, G. Z. S., Reyes, P. G. A. D., & Samson, B. P. V. (2020). From Access to Effective Use: Open Data Portals for Everyday Citizens. ACM International Conference Proceeding Series, pp. 61–64

Concannon, D., Herbst, K., & Manley, E. (2019). Developing a data dashboard framework for population health surveillance: Widening access to clinical trial findings. Journal of Medical Internet Research.

DATALIT. (n.d.). DATALIT, https://datalit.pa.itd.cnr.it/pt/ (April 5th, 2021).

Figueiras, A. (2015). Towards the understanding of interaction in information visualization. Proceedings of the International Conference on Information Visualisation, pp. 140–147

Gebre, E. H., & Morales, E. (2020). How "accessible" is open data?: Analysis of context-related information and users' comments in open datasets. Information and Learning Science, pp. 19–36.

Géryk, J. (2015). Using Visual Analytics Tool for Improving Data Comprehension. Proceedings of the 8th International Conference on Educational Data Mining, pp. 327–334.

Lee, T., Lee, B. K., & Lee-Geiller, S. (2020). The effects of information literacy on trust in government websites: Evidence from an online experiment. International Journal of Information Management

Munzner, T. (2014). Visualization Analysis and Design. In Visualization Analysis and Design.

Oghbaie, M., Pennock, M. J., & Rouse, W. B. (2016). Understanding the efficacy of interactive visualization for decision making for complex systems. 10th Annual International Systems Conference.

Pothier, W. G., & Condon, P. B. (2019). Towards data literacy competencies: Business students, workforce needs, and the role of the librarian. Journal of Business and Finance Librarianship, pp. 1–24.

Raffaghelli, J. E. (2020). Is data literacy a catalyst of social justice? A response from nine data literacy initiatives in higher education. Education Sciences, pp. 1–20.

Rodrigues, A. M. B., Barbosa, G. D. J., Lopes, H. C. V., & Barbosa, S. D. J. (2020). What questions reveal about novices' attempts to make sense of data visualizations: Patterns and misconceptions. In Computers & Graphics.

Rouse, W. B., Pennock, M. J., Oghbaie, M., & Liu, C. (2017). Interactive visualizations for decision support: Application of Rasmussen's abstraction-aggregation hierarchy. Applied Ergonomics,

pp. 541–553.
Zhu, Y. (2007). A Review of the Current Definitions of Effective Visualization. Information Visualization, pp. 652–661.