## USER ASPECTS OF DATA VISUALIZATION IN OFFICIAL STATISTICS

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### **Abstract**

Official statistics data are generally considered of high quality. Visualization of these data, however, seems to be lagging behind. As sound methodology should also be used for data visualization, we first introduce some theoretical background of data visualization research. We argue that effectiveness of graphical displays in official statistics should be judged from a user perspective. We present preliminary results of the study that tested some aspect of data visualization effectiveness in an unexperienced group of first-year undergraduate students. Our work-in-progress proposition is that one-size-fits-all approach has to be acceptable for all users of official statistics, which is currently not. Tailored solutions should be more effective only when visualization targets specific user groups.

# 1 Introduction and theoretical background

Official statistics has a long tradition of providing its services to government for policy making and analysts in different fields (research institutes, academia, business), but in the course of the past decade we can observe official statistics turning to the general public as well. The recognition of a wider audience was presumably enhanced by increasing demand for open, transparent data and emergence of data journalism. Moreover, the development of information society supported the process by offering new technological solutions for accessing and communicating data. Data visualization, probably one of the most common method of communicating statistical information, has thus been deployed to official statistics dissemination. Although our research tests and evaluates data visualization in official statistics from the perspective of data presentation, the role that visualization tools play in exploratory and confirmatory analysis should be acknowledged as well.

It might be tempting to think that nothing can go wrong when visualizing data since "picture tells more than a thousand words". Research findings and practical experience (e.g. Kosslyn, 2006; Few, 2008) point out numerous drawbacks. *Data visualization* can indeed convey data and allows us to *gain quicker and deeper insight* and understanding of data relationships. However, this aim is only fulfilled when precautions are taken into consideration, since data visualization can just as well *distort data and mislead us* to wrong conclusions. Numerous research areas, such as statistics, psychology, computer science, semiotics, graphical design, cartography, art, and educational research have contributed to establishing data visualization guidelines (e.g. Tufte, 1991; Kosslyn, 2008) and proposing models of chart perception, comprehension and interpretation (e.g. Shah & Hoeffner, 2008; Hegarty, 2011; Ware, 2004).

Early research in the field of data visualization primarily addressed the question of graphical perception, where the impact of visual encodings such as position, length, area, shape, and colour was investigated. Cleveland and McGill (1984) proposed the ranking of effectiveness of these visual variables – described as pre-attentive attributes – suggesting that certain properties are identified

with greater speed and easiness. Assessment of response time and accuracy for values estimation tasks lead authors to label pie charts and stacked bar charts as ineffective data visualization displays.

The choice of a graphical display significantly shapes our perception of graphical elements and consequently affects our interpretation of data. Nevertheless, a great deal of the research identified additional factors that appear to influence comprehension of graphs, implying that the process involves interaction of both visual perception and *memory processing* (Kosslyn, 2008; Shah & Hoeffner, 2008). Task performance can be different with different visual displays of the same information and displays that are effective for one task may be ineffective for another (e.g. Spence, 1991; Gillan & Richman, 1994; Gillan, 1994; Shah & Carpenter, 1995; Tversky et al., 1999). For example, tables are most efficient when exact numbers should be extracted, while charts enable us quickly and easily judge proportions, notice trends, or convey relationships. Research focus has thus shifted from observing visual perception of graphical elements to *understanding the process of data interpretation*. In this complex sequence of cognitive processes, a number of sub-processes can be named, such as pattern perception, memory of images, spatial reasoning, and knowledge of semantic content. The latter indicates that apart from the characteristics of graphic formats, content domain characteristics in general and data sets characteristics in particular should also be acknowledged in the chart comprehension process.

Moreover, when we try to derive meaning of data that is represented by graphical elements, our perception and cognition are in many ways limited and prone to biases, adding additional accounts to be taken into consideration when visualizing data (Lohse, 1995). Failure to respect human cognitive capacity might hinder any other attempts to improve graphic display.

Recently, insights in the area of data visualization have called for re-interpretation of data visualization effectiveness (Few, 2017; Camoes, 2017). Accuracy and speed of information processing, two assessment criteria that are widely adopted in data visualization research, arguably fail to evaluate *multiple perspectives of chart effectiveness*. Several additional criteria are thus proposed, such as usefulness, completeness, perceptibility, truthfulness, intuitiveness, aesthetics, and engagement (Few, 2017). Furthermore, effectiveness of the data visualization does not solely include effectiveness of the perception and interpretation process, but it should also address effective communication of the message (Camoes, 2017; Nussbaumer Knaflic, 2015).

Following this line of reasoning, we argue that the data visualization message might not have the same effect on all the users. Apart from taking into account human perception and cognitive processing, there are also several other factors that presumably contribute to the user experience with data visualization. Individuals differ in their domain knowledge, statistical literacy and numeracy, educational background and previously acquired experience, expectations and attitudes, motivation and goals.

Official statistics data might serve various purposes and different audiences. However, we believe that specific characteristics of these audiences – or user groups – seem not to be always taken into consideration when disseminating official statistics data. We distinguish between *three major official statistics user groups: general public, decision makers and analysts.* Our understanding of their characteristics closely resembles the classification of data warehousing users (Inmon, 2005; Ponniah, 2001): tourists, farmers/harvesters and miners, respectively. Tourists are usually looking for basic data, driven by curiosity, while farmers/harvesters are more goal oriented, looking for data to support their research or economic decisions. Miners are the most proficient users, requesting detailed and complex data. There have already been some attempts to adopt this classification to official statistics setting (Grossenbacher, 2007; Vale, 2008).

If user groups differ in their knowledge, experience, attitudes and motivation, then we can assume that the process of chart comprehension would differ among them as well. Consequently, the *take-away message* and the whole experience with data visualization might not be the same for general public as compared to other user groups. The effectiveness of data visualization would thus depend on the graphical characteristic of a chart display, content domain requirements, and data set characteristics, while knowledge, both domain and statistical, as well as experiences and skills in the field, would mediate the process. Furthermore, we assume that motivation and attitudes might act as moderators in the process of conveying data visualization message.

#### 2 Data and methods

We present some preliminary results of our research on user aspects of data visualization in official statistic. However, it should be noted that this is a work in progress and the insights and plans we offer hereby are still in the process of formation.

In the first round of the research we conducted three pre-tests. Participants were international first-year students of an introductory statistics course at the Faculty of Economics, University of Ljubljana; about half of them Slovenian while the rest named 30 other countries of origin and/or study. The number of participating students was different over three trials, the first involving 79 participants, the second one 46, and the third one 70. There was almost a gender balance in each of the pre-tests and most of the participants were around 20 years old.

In the first pre-test (see Figure 1), participants were given six tasks that called for six different data visualizations (bar chart, histogram, line chart, pie chart, scatter plot and table). Participants were unaware of the right choice and were asked to select the most appropriate display for the task among the six proposals. The order of proposal presentation was randomized. Once selected a display format, participants were requested to make an addition choice, this time presented with particular variations of the previously chosen display (for example, minimalistic version of the display, 3D version, display with gridlines).



Figure 1: Display of one of the six tasks

In the second pre-test (see Figure 2), participants were instructed to answer a question, based on the data presented. Again, we tested six different tasks (extracting a number, ranking, estimating differences and proportions, describing trends and relationships). Participants were randomly assigned to one of three different displays for each of the tasks. In both the first and the second pretests, tasks and displays were (at least partly) de-contextualized in order to avoid the effect of previously acquired domain knowledge or possible expectations (e.g. labels Country 1, Country 2, etc. were used instead of country names).

# DataVisualization\_Test2 In the following display we present adult population structure of a selected country by four employment categories. How large is the share of unemployed in the population? Adult population structure 30 \*Your answer: \*Please evaluate the presented visualization on four characteristics using a 7-point scale. Useless for the task 0 0 0 0 0 Useful for the task 0 0 0 0 All relevant data given No relevant data given 0 0 Difficult to understand 0 0 0 0 0 Easy to understand Not interesting 0 0 0 0 0 0 Interesting Previous page Next page

Figure 2: Display of one of the six questions

In the third pre-test (see Figure 3), we used *examples of Eurostat's data visualization*. We chose displays as typical representatives of usual data visualizations in official statistics. The displays were applied in their original format. Participants were asked to list *the first three things they see* when looking at the display. In the second and third pre-test all of the displays were followed by a 7-point bipolar scale, *estimating the usability of the data visualization* on the following criteria: usefulness, relevant data, easy to understand, and interesting.



Figure 3: Display of one of the four examples of Eurostat's data visualization

## 3 Results and discussion

The first pre-test showed that in most of the cases students *opted for the most appropriate display for the given task* (e.g. bar chart to rank data, line chart to present trends). However, when asked to choose a particular version of the selected format, they did not always prefer the displays that would meet "the simplest graph" guideline as proposed by Tufte (2001). Rather, participants tended to choose displays with gridlines, tables with colors and 3D displays of bar charts (3D histograms and pie charts remained unselected). Similar findings were reported by previous studies (Levy et al., 1996; Fisher at al., 1997; Inbar et al., 2007). These users seem to *prefer displays with some unnecessary graphical elements* – or "chartjunk" in Tufte's terms.

Results of the second pre-test are also in line with previous studies (Cleveland & McGill, 1984; Simkin & Hastie, 1987; Spence, 1991). Task performance was evaluated with correct answers and scores on usability characteristics scale. The line chart was an effective display when describing data trends. The pie chart was largely inefficient at the ranking task while the value estimation performance was better in comparison with the stacked bar chart. Overall, the *simple bar chart had the best task performance*.

In the first and second pre-test, participants experienced most difficulties with describing data correlation (or the absence of it) and comprehending scatter-plot display. The most plausible explanation seems to be the lack of experience that the first-year students have with the more advanced statistical concepts. This finding indicates the role of (statistical) knowledge in the graph comprehension process. Similar observations can be drawn from the results of the third pre-test. Some participants commented that they did not understand a rather simple bar and line chart, so it was probably insufficient domain knowledge that prevented the participants from providing answers.

As previously mentioned, official statistics data visualizations were mainly in the bar chart format and therefore presumably rather unproblematic to interpret. However, our analysis points out that grouped bar charts were not always easily comprehended. Furthermore, our findings suggest that the role of chart title should be stressed. One of the tested visualizations had a title that appeared to be misleading to some of the participants, resulting in data interpretations that were completely wrong.

Another typical display of official statistics data dissemination is a chart map. We compared interpretation of the same data set, presented in two formats, either as a bar chart or a chart map. Participants were more prone to note the countries with extreme values or even to extract some concrete numbers from a bar chart. On the other hand, when observing the chart map, they tended to make more comparisons or even tried to find some rules that would apply to data. Again, these findings support our theoretical background that the choice of a data visualization display affect the graph comprehension and interpretation.

## 4 Further steps

Our aim is to further empirically research the impact of selected factors (e.g. graphical elements, content and domain characteristics, statistical and domain knowledge). The testing will be conducted on graphical displays in the field of official statistics by including other user groups with other combinations of impacting factors (e.g. decision makers and analysts) compared to the first-year students that presumably reflect the characteristics of the general public. If the tests show that data visualization effectiveness is different for different user groups, we will propose to adjust the current one-size-fits-all approach to be acceptable for all users of official statistics (except if only a specific user group is targeted).

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