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Aesthetics and Usability of Statistics Data Visualisation through Charts: An Eyetracking Study as a Tool for Chart Analysis

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Abstract:

Purpose: *This study focuses on identifying key factors influencing the choice of certain types of data visualizations in an economic context, emphasizing aesthetics and usability. The study used eyetracking technology to analyze users' interactions with different types of charts, bar, line, pie and dot plots.*
Design/methodology/Approach: *The experiment involved 34 participants, who studied datasets from Eurostat showing the volume of fish catches and grain production in selected countries. An eyetracking analysis showed that critical visualization elements, such as titles and figures on axes, attracted the most attention from users. Bar charts proved to be the most intuitive and readable visualization format, as confirmed by both eyetracking data and survey responses. Line and dot charts, however, posed interpretive challenges for participants, highlighting the need for further refinement. Pie charts were appreciated for their ability to depict proportions, although they required more user involvement in interpretation.*
Findings: *The findings underscore the importance of appropriate visualization design for effective data communication. Key aspects include the use of aesthetically pleasing elements, appropriate color contrast and intuitive structure to increase user engagement and facilitate data interpretation. In particular, users preferred bar charts for their simplicity and ability to clearly represent categories, while pie charts were preferred for showing proportional data. Point and line charts, on the other hand, were less intuitive for data spanning multiple categories.*
Practical implications: *The study also highlights the importance of integrating visual elements, such as titles and labels, to improve usability and comprehension. The insights from this study can help designers create data visualization tools that meet user needs more effectively, supporting better decision-making in fields such as economics, statistics and business.*
Originality value: *These findings provide a basis for further investigation of user interaction with different visualization formats, emphasizing the need to tailor design to user preferences to optimize data presentation and communication.*

Keywords: *User experience, usability of the charts, data visualization, statistical and economic data, data management.*

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1. Introduction

Modern research is characterized by an increasing emphasis on effective data representation (Lübke *et al.*, 2021; Fairbairn and Hepburn, 2023; Kremsner *et al.*, 2023; Novák *et al.*, 2024). Economic, business, statistical or demographic data are often complex, encompassing multidimensional sets of information, and their effective visualization is becoming a key element to support decision-making and analytical processes (Lübke *et al.*, 2021; Novák *et al.*, 2024).

Graphs, such as bar charts, pie charts and line graphs, are commonly used data visualization tools because of their ability to present information in a concise and clear manner. However, their usefulness and effectiveness are not just a matter of choosing the form of the chart, but also result from the appropriate application of visualization principles, such as color theory, spatial layout and visual perception research methodology.

A modern approach to creation is key to achieving content that is optimised for readability as well as comprehensibility. The use of qualitatively appropriate graphs of various types or maps allows the viewer to understand the data presented without the need for extensive explanations of their meaning. (Kremsner *et al.*, 2023). Charts as graphics also have an impact on the communication of information. Thanks to them, we can convey certain data to the recipient, recognising that the message will be comprehensible to them.

When designing a graphic or infographic for the recipient, the designer himself must determine all the elements that make up the whole. Despite previous research and guidance on chart design, there is still a limited understanding of how people read and compare data on infographic graphics (Goldberg and Helfman, 2011). It is therefore of paramount importance to design charts that present data in a way that allows the data to be communicated to the end user as effectively as possible.

When it comes to visualising data of various types, the essence is to build charts in a way that allows for data analysis, business decision-making and prediction in relation to future trends (Nash *et al.*, 2022; Marques Santos *et al.*, 2023; Nærland and Engebretsen, 2023; Madsen, 2024). The key elements influencing the perception and interpretation of the charts are the colours, and moreover the colour preferences of the audience can influence their final perception (Schloss and Palmer, 2011; Ware, 2019). Appropriately selected colours can, for example, indicate key data or accentuate differences between categories, making the material more intuitive to perceive (Midway, 2020). Thus, inappropriate use of colours, such as the use of palettes that are not calibrated with each other in terms of colours or that are too complex, can lead to misinterpretation of data by the viewer (Crameri *et al.*, 2020).

Understanding the combination of colours, charts and all the information associated with them cannot take place without the concept of usability as well as user experience (UX). Constant changes in technology, demographics and sociology require constant research into data visualisation in order to make it as easy as possible for viewers to read the data in the graphs, but at the same time provide them with all the necessary data to understand the issue presented (Elavsky *et al.*, 2022; Scheuer and Torous, 2022). A poorly constructed chart will not only fail to deliver any message to the recipient, but will additionally make it difficult for the recipient to understand it as a whole.

Analysis of visualisation, colour combinations, chart types, fonts or element requirements (e.g. size) is an extremely important factor in order to best communicate data to the audience. Adapting elements to increase their readability is a building block not only to the quality of the message, but also to ensure a high level of user experience when using such materials (Zong *et al.*, 2022; Rui *et al.*, 2023).

The aim of this paper is to identify the key factors influencing the selection of a particular type of chart with economic data. As part of the study, an eyetracking analysis was conducted on prepared charts containing data downloaded and prepared from the Eurostat website. The results of the study aim to better understand the strategies for preparing better usability charts, so that any information they convey is best understood by the viewer.

The author's hypothesis is that an aesthetically pleasing and intuitive data visualisation design, taking into account appropriate element placement, colour contrast and readability of information, increases user engagement, improves their ability to interpret the data and influences their preference to select specific chart types depending on the content presented.

2. Literature Review

Data visualisation is an integral part of fields related to economics, statistics, demography, sociology or biology, among others (Few, 2009; Goldberg and Helfman, 2011; Godfrey *et al.*, 2018; Riffe *et al.*, 2021; O’Donoghue, 2021; Bondarenko *et al.*, 2022). Analysing data in these areas using graphs not only makes it easier to visualise the issues, but can also enable information to be communicated more easily. The use of a graph for this purpose involves the appropriate selection of its data structure.

These structures are still evolving today in response to the diversity and complexity of the data. The following is an overview of the most important types of visualisation and their applications in the context of data types, based on the latest research, compiled from publications (Few, 2009; Goldberg and Helfman, 2011; Healy, 2019; Danisch and Krumbiegel, 2021; Waskom, 2021; Wang *et al.*, 2021; O'Donoghue, 2021; Gu, 2022; Kalinin *et al.*, 2022; Chen *et al.*, 2022; Marques Santos *et al.,* 2023; Nærland and Engebretsen, 2023; Madsen, 2024):

Line graph **-** a basic form of data visualisation that is represented as variable values in a continuous variable defined by the data. The data is represented as points connected by either a continuous line or a continuous line with no points clearly indicated. These charts make it easy to follow trends or fluctuations, but also allow for the presentation of e.g., population growth, temperature change, sales values. The simplicity of these charts makes it possible to present changes in a particular sector such as economics, demography or meteorology in an easy and clear way. It should be noted, however, that these charts may not work when there is little data or when the values between successive points vary significantly.

Bar chart **-** a type of chart used to compare values within or between categories. They are used, e.g. number of students in different departments of a university, sales by region. Among them, a distinction is made between grouping, e.g. by sum or by category. Such charts can be divided into vertical and horizontal.

Pie chart **-** these show data in the form of a circle or a circle divided into slices. They can be joined together or pulled apart to show differences. They are used to show percentage breakdowns. Despite their popularity, they do not allow easy comparison of slice sizes. When the data vary too much in size between them, it is extremely difficult to obtain visible circle or circle slices for small values. This renders such a graph useless, as the difference in the data cannot be observed.

Dot plot **-** is a tool to examine the relationship between two quantitative variables on two axes. Points on a graph are used to observe clusters, outliers. They are often used in the visualisation of mathematical and statistical data, but also in the field of economic data. Examples of use are the visualisation of growth, weight, income, etc. These graphs are extremely simple to implement.

Layer chart **-** is a variation of the line chart, differing in that the area under the line is painted over. It represents cumulative values over time, e.g. the income structure in a particular sector or region, but also changes in the market share of a particular product.

Histogram **-** a particular graph used to represent the distribution of numbers within a given range. Most commonly, the horizontal axis is used as a division into intervals and the vertical axis is used to represent the frequency of values within each specified interval. These histograms are used, for example, in statistical analysis, cluster analysis or data analysis - examples of applications include the distribution of exam results.... The disadvantage of these graphs is the different interpretation depending on the width of the intervals chosen and the data used.

Another type of graph can be a *heat map.* A specific data visualisation particularly useful for large datasets. It uses colours to present the differences in a given set. It is most often presented as a two-dimensional matrix divided into rows and columns. Each cell of such a matrix is a combination of values from a given row and column.

The given values calculated for each cell are finally normalised and then translated into the calculated colour scale, e.g., green for the lowest values and red for the highest. These graphs are used, for example, in business analysis for the visualisation of specific indicators, in correlation analysis between variables, but also in eye-tracking to represent the areas most frequently viewed by subjects on a given stimulus.

Usability is inherent in the use of any product, not just websites, operating systems, services, companies, etc. Usability as a whole refers to the measure of how effectively, efficiently and satisfactorily a product is used by certain users to achieve certain related goals (Nielsen, 1993; CSRC Content, n.d.; Borawska and Mateja, 2024). Usability focuses on the premise of minimising the difficulties users may encounter when interacting with the product.

Following Nielsen or Norman, it is assumed that usability also defines the ease of understanding a given product, the speed of learning how to use it, how easy it is to remember how a given system works and how easy it is to recall this information, how easy it is to correct user errors, but also the satisfaction of using a given product ("ISO 9241-210:2010(en), Ergonomics of human-system interaction — Part 210: Human-centred design for interactive systems," n.d.; Nielsen, 1993; Norman, 2013). Furthermore, not only in ISO 9241-210, but also in scientific publications, researchers state that an integral part of usability is User Experience (UX) ("ISO 9241-210:2010(en), Ergonomics of human-system interaction — Part 210: Human-centred design for interactive systems," n.d.; Borawska and Mateja, 2024).

It can therefore be seen that usability, or UX as a whole, for charts of various types will be defined as the ability to communicate data in a clear, concise and easily digestible manner (Hartson and Pyla, 2012; Vande Moere *et al.*, 2012; Mauri *et al.*, 2021). Furthermore, charts must be designed to be as clear as possible in terms of clearly presented data, precise in terms of data interpretation and minimalist in that they are limited to only the necessary visual elements (Few, 2009; Cairo, 2013; Norman, 2013).

Charts should be designed to help users quickly understand the data, its relationships and trends. It is important that charts are clear and well-organised, and do not contain unnecessary elements that may distract the user's attention (Tufte, 2018). It is also crucial to choose the right types of graphs for the data presented (Evergreen, 2019; Luo *et al.*, 2019). Thus, the appropriate selection of the chart for the data used by the author is the key to obtaining a useful chart in terms of data communication.

Two key elements of the charts that cannot be overlooked are the colour scheme and the architecture of the charts. For charts, the colour scheme is an essential element, it creates a correct interpretation of the data and allows the data to be prioritised (Brewer, 1994; Ware, 2004). Colours can influence the decisions of the audience and should therefore be chosen thoughtfully and in line with human visual perception, while inappropriate colour choices can confuse the user (Ware, 2019). Colours should not be too bright or too pale to avoid visual fatigue for users (Norman, 2013).

Colours close to or equal to red can be identified not only with something warning, but also with energy or passion - which translates into attracting attention, for example. Yellow is associated with a warning, and blue, for example, can be associated with a feeling of calm or build confidence - this is called cultural symbolism or colour symbolism. In addition, contrast between colours, including the background, is an important element, allowing for increased digestibility of information and readability itself.

In addition to contrast and colour symbolism, there is the concept of accessibility, i.e., enabling people with, for example, Daltonism to read the content of such a chart (Spence, 1990; Brewer, 1994; Cyr *et al.*, 2010; Stone, 2016; Ware, 2019). Chart architecture is the process of designing and adapting the type, content, elements and visual features of a chart to the content it is intended to convey (Kirk, 2019). The whole process of designing such a chart consists of elements, development on the basis of Zeng (2009), Munzner (2014), Kirk (2019) and Evergreen, (2019).

The first step is the selection of the structure, which involves choosing the layout but also the size and scale of the axes to keep them legible and proportional. The second step is to reduce unnecessary visual elements in order to minimise only key data. The third step is to use appropriate colour and contrast to maximise readability. The fourth step is to prepare a chart tailored to the audience's knowledge and perceptual capabilities. In summary, therefore, psychology as well as colour theory is an essential element in order to develop appropriate chart preparations that meet requirements.

3. Research Methodology

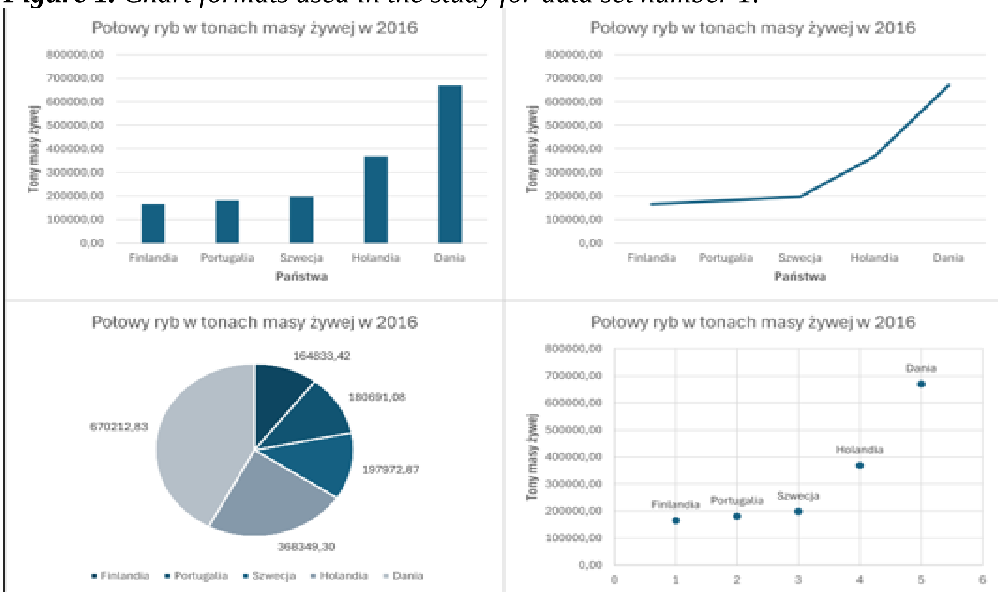
This paper uses an experimental case study to investigate user behaviour when interacting with different types of charts representing selected statistical data. The study focused on evaluating the usability of the charts. Participants in the study evaluated their design and usability, and identified elements for improvement. On the basis of a declarative comparison using a questionnaire, they determined which chart they thought was the best in relation to the data used.

Participants:
Thirty-four people (12 of each sex) aged 19-58 took part in the study, which is a classic sample size for eye-tracking experiments in UX research (Vasseur et al., 2019). The mean age was 32.55 years (SD = 12.33). All participants were healthy and saw correctly.

Research materials:
During the study, participants viewed 8 charts presenting data downloaded and analysed from Eurostat ("Statistics - Fishery | Eurostat," n.d.; "Statistics - Grain | Eurostat," n.d.). The data concerned fish catches in tonnes live weight in 2016 for 5 selected countries - Finland, Portugal, Sweden, the Netherlands and Denmark, and grain production in 2017 for 5 selected countries - Slovenia, Estonia, Belgium, Finland and Denmark.

As the study was about the presentation of the data and not the data itself, the countries were randomly selected. All graphs were designed in a similar way to classic charts, but the colour of the presented data was limited to blue to leave a neutral colour with the highest possible aesthetics (Hall and Hanna, 2004; Cyr *et al.*, 2010; Grant, 2018; Fairbairn and Hepburn, 2023). Figure 1 below shows the 4 chart formats for the first set of data.

Figure 1. *Chart formats used in the study for data set number 1.*



Source. *Own elaboration.*

The graphs were presented in identical form for both sets of data i.e. - bar chart, line chart, pie chart with division and dot plot in the first instance.

Research procedure:
The study was conducted with the approval of the Bioethics Committee of the Regional Medical Chamber, according to an established research procedure developed by the (Borawska and Mateja, 2024). The procedure involved preparation, conducting the experiment and collecting feedback from participants. The whole process took about 10 minutes per person, providing a comprehensive analysis of user behaviour in the context of the graphs and data visualisations, allowing a detailed assessment of their functionality and aesthetics.

After preparing the test site, each participant was presented with the stimuli in the form of graphs - 8 graphs in the same order. After completing the tasks on the site, participants completed a survey in which they evaluated the graphs and answered questions related to the data presented. Respondents gave their opinions on the graphs, indicating which were the best, and identified elements that made the graphs unreadable or incomprehensible to them. In addition, participants declared whether they had previously been exposed to the topics of the data used and whether they were interested in any of the fields.

Collection and processing data:
To measure eye movements, a GazePoint GP3 60HZ eyetracker was used, mounted under a 24-inch full HD (1920 x 1080 pixel) monitor on which the stimuli were presented. During the study, data acquired during the recording of the biological signal from eye movements was collected. Heat maps were created from the signal and areas of interest (AOIs) were delineated, covering the chart elements under study. The entire signal analysis including the delineation of heat maps and AOI areas was done using GazePoint software.

Measures values:
Classical eye-tracking measurement involves the analysis of the two elements of fixation (points on which the test subject focuses his or her gaze and reads the data) and saccades (rapid eye movements between fixation points)(Poole and Ball, 2005; Pedersen, 2007; Białowąs, 2021; Mateja, 2023). Through fixations and saccades, several basic metrics of the eye tracking study can be determined.

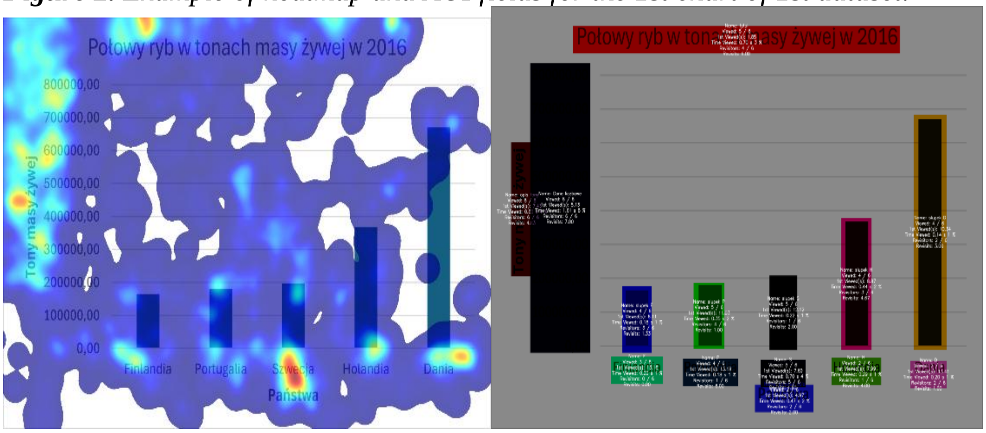
One of the metrics analysed was the average time spent in the area of interest (AOI), which shows how long users focus on specific elements of the stimulus (Joseph and Murugesh, 2020; Da Silva Soares *et al.,* 2023). Another important indicator was the TTFF (time to first fixation), i.e. the time that elapses from the moment the stimulus is presented until the user first directs his or her gaze to the particular area under study (Poole and Ball, 2005; Cho *et al.,* 2019). The number of revisits, in which the user returns again with his or her eyes to a previously viewed item, was also examined (Cho *et al.,* 2019; Badenes-Rocha *et al.,* 2021).

4. Research Results

The results take into account the analysis of the participants' responses to the post-study survey, as well as the processing of the data recorded during the experiment using an eye-tracking device.

Analysis of eyetracking data:
The analysis of heat maps and areas of interest will be broken down below into separate descriptions for each diagram. The results for the first data set will be presented first.

Figure 2. *Example of heatmap and AOI fields for the 1st chart of 1st dataset.*



Source: *Own elaboration.*

Bar Chart - the visualisation in the form of a bar chart shows fish catch data for selected countries in 2016. The title of the graph was one of the main points of interest, noticed by 30 users, with a viewing time of 700 ms. The average time to first look (TTFF) of 1850 ms indicates that the title quickly attracts attention. The number of returning users (18) and the return rate (4.5) underline its importance as an introductory element.

The description of the vertical axis and the figures were the key elements of the visualisation, noted by 34 users. The numerical data were analysed for 1600 ms and the axis description for 850 ms, indicating their importance in the interpretation of the data. The return rate for the numerical data was 7, highlighting their key role in the analysis. In terms of individual bars representing countries, Denmark and the Netherlands attracted the most attention. The Denmark post was viewed by 32 users for 140 ms and the description of this country was noticed by 30 people for 200 ms.

The Netherlands' post, on the other hand, attracted the attention of 32 people with a viewing time of 440 ms, making it one of the more engaging elements. Other countries such as Finland and Portugal generated moderate interest - their posts were analysed for 180 ms and 350 ms respectively. The description of the Swedish post, despite being noticed by 34 users, stood out for its relatively low viewing time (220 ms), but a return rate of 2 shows its higher value. The vertical axis figures and the Denmark and Netherlands posts were the most engaging elements of the graph. Countries such as Finland and Portugal generated less interest, which may be due to the lower relevance of their data in the analysis.

Line chart - like the bar chart, presents fish catch data, but allows for a clearer visualisation of trends between countries. The title of the graph alone attracted the attention of 32 users, who spent an average of 1580 ms analysing it. The return rate of 6 and the number of returning users (31) confirm that the title played a key role in introducing the data analysis. The figures on the vertical axis proved to be the most engaging element of the graph. They attracted the attention of 34 users, who spent as much as 4510 ms on their analysis.

The return rate (6.2) further underlines their relevance for interpretation. In contrast, the graph line, representing the trend, was the most noticeable element of the visualisation - it was analysed for 4160 ms on average, making it the focal point of attention. The points on the graph representing each country also generated different levels of interest. Denmark's point was the most engaging, noticed by 34 people, devoting an average of 1040 ms to it. Finland's point, although noticed by 32 people, attracted slightly less attention, with a viewing time of 740 ms. The points representing Slovenia and Estonia attracted the least interest, with their analysis taking users an average of 620 ms and 560 ms respectively.

Pie chart - the title of the chart was noticed by 31 people who spent an average of 1350 ms analysing it, with a high return rate of 6.2. Although the TTFF of 2940 ms indicates that the title was not the first element to attract attention, it played a key role in users' orientation. The main part of the graph (the circle) attracted the most engagement, which was analysed for 3360 ms, with a return rate of 8.6 and a number of returning users of 32. This highlights that users treated the graph as a key visualisation element.

The figures and bars representing countries had different levels of engagement. The data of Finland (450ms) and Denmark (570ms) stood out the most, with 33-34 users analysed. Country descriptions such as Portugal and Sweden attracted shorter attention spans (310 ms and 600 ms respectively) and generated lower return rates, indicating that users focused more on the graphical elements than on the detailed descriptions. In summary, the most important elements of the graph were the circle and the figures of Finland and Denmark, which attracted the most attention. Country descriptions generated less interest, particularly for the Netherlands, suggesting that users appreciated the direct numerical information more than the textual details.

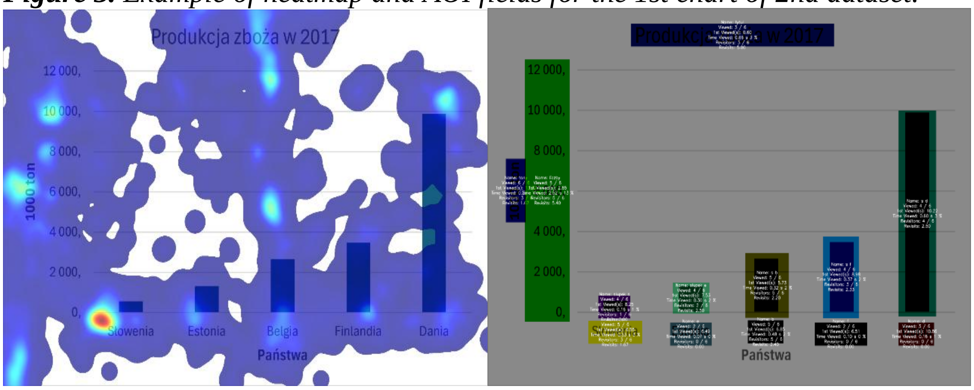
Dot plot - The heatmap dot plot illustrates the distribution and intensity of users' attention on different elements of the visualisation. The title of the graph attracted the attention of 33 users, who spent an average of 810 ms analysing it, with a high return rate of 6.6. The Time to First Look (TTFF) of 1250 ms indicates that the title was one of the first elements analysed by users. The figures on the vertical axis were the most engaging element of the visualisation, noticed by 34 people for an average of 850 ms. The return rate (3.17) and the short TTFF (5400 ms) highlight their importance as a key point of data interpretation.

The description of the vertical axis, although noticed by 34 users, generated a shorter analysis time of 350 ms, indicating that users quickly absorbed this information and focused on the other elements. The points representing each country generated different levels of interest. Portugal's point stood out with the highest viewing time of 800 ms, with a return rate of 3.8, indicating high information value.

Denmark and the Netherlands attracted users' attention for 710 ms and 510 ms respectively, with a return rate of 31 and 30. The point of Finland was analysed by 33 people, but the average viewing time was only 540 ms, suggesting that users considered this data less relevant in the context of the overall visualisation. Sweden's point, although noted by 34 people, attracted moderate interest with a viewing time of 500 ms.

The analysis of heat maps and areas of interest will be broken down below into separate descriptions for each diagram. The results for the second data set will now be presented:

Figure 3. *Example of heatmap and AOI fields for the 1st chart of 2nd dataset.*



Source: *Own elaboration.*

Bar Chart - The title of the chart was noticed by 31 users, spending an average of 660 ms on it. The return rate (5) and 21 returning users highlight its importance as an introduction to the analysis. Although the vertical axis description caught the attention of 34 people, the average viewing time of 175 ms indicates that it was quickly understood and did not require further analysis. The figures on the vertical axis stood out as one of the key elements of the visualisation. They were noticed by 33 users, who spent as much as 2520 ms analysing them, confirming their importance in interpreting the results. Turning to the detailed analysis of the individual bars, the data for Belgium and Denmark generated the most interest.

Belgium's post was noticed by 34 people with a viewing time of 320 ms and a return rate of 2.2. The description of this country had higher engagement with an average viewing time of 480 ms and 31 users returning to it. In contrast, the Denmark post attracted the attention of 29 people with a viewing time of 600 ms, making it the most engaging element.

It is worth noting that Denmark's description only generated 160 ms of attention, which may indicate limited interest in the details. Other countries, such as Estonia and Finland, attracted less interest. The posts of Estonia and Finland recorded 300 ms and 370 ms of average viewing time respectively, indicating moderate interest. The descriptions of these countries also generated shorter engagement times of 110 ms and 100 ms respectively. Slovenia, despite being analysed by 32 users, stood out with the shortest post viewing time (160 ms) and a limited number of returns.

Line graph - The title of the graph was noticed by 33 users who spent an average of 2250 ms analysing it. A return rate of 5.2 and 31 returning users underline its relevance as an introductory element. The vertical axis description was less engaging - it was noticed 31 times and the average analysis time was 240 ms. The figures on the vertical axis were a key element of the visualisation, attracting the attention of 34 users for a duration of 2190 ms, confirming their importance in interpreting the data.

The most engaging element of the graph was the trend line, which was analysed for 4160 ms. The number of returning users was as high as 33, and the return rate of 9.8 demonstrates the key role of this element in the analysis. The points on the graph, representing each country, generated different levels of interest. Belgium's point was spotted 33 times with a viewing time of 660 ms and a return rate of 3.5, making it one of the more engaging. Finland's point attracted 32 users with a time of 740 ms and a return rate of 3.2, also indicating high interest. Denmark's point was the most analysed - it was noticed 34 times with a viewing time of 1040 ms and a return rate of 2.

In contrast, Slovenia and Estonia's points attracted less interest. Slovenia's point was noticed 31 times, but the average viewing time was only 620 ms. Estonia attracted 33 users, but its point was analysed for 560 ms on average, indicating moderate engagement. In summary, the trend line and the points representing Belgium, Finland and Denmark were the key elements of the graph, while the points of Slovenia and Estonia generated less interest.

Pie chart - The title of the chart was noticed by 30 people who spent an average of 1060 ms analysing it. A return rate of 6.4 and 28 returning users confirm its importance. The main part of the graph, the circle, was the most engaging element of the visualisation. It was noticed by 34 users, who spent as much as 3430 ms on its analysis. The number of returning users (34) and the return rate (5.17) underline its key role. The figures for the countries generated different levels of interest. The figures for Slovenia and Denmark were the most engaging, with 1260 ms and 410 ms of viewing time respectively.

Belgium and Estonia captured users' attention for an average of 650 ms and 200 ms, indicating their moderate importance in the analysis. Finland, despite being analysed by 33 people, stood out as having the shortest viewing time for figures - only 140 ms. Country descriptions generated significantly less interest than figures. The description of Denmark was noticed by 31 people, but the average analysis time was only 120 ms. Similarly, the description of Finland attracted the attention of 29 users, who spent an average of 240 ms on it.

Spot chart - The title of the chart attracted the attention of 33 users who spent an average of 680 ms analysing it, with a return rate of 2.75. The time to first look (TTFF) of 5890 ms suggests that the title, despite its importance, was not the first element analysed by users. The figures on the vertical axis were the most engaging element of the graph, capturing the attention of 34 people for an average of 2830 ms.

A high return rate of 2.4 and a shorter TTFF (5170 ms) indicate that users appreciated the key numerical information to interpret the data. The description of the vertical axis, although noted by 28 people, generated a shorter analysis time of only 180 ms, indicating its lesser role in interpretation. Denmark was the most engaging item. It was noticed by 34 people, with an analysis time of 1040 ms, indicating a high information value.

Belgium also attracted the attention of 34 users, but the viewing time was shorter (660 ms), despite a high return rate of 3.5. Finland was analysed by 32 people for 740 ms, indicating moderate interest. Estonia and Slovenia attracted the attention of 33 and 31 users respectively, but their viewing times were 560 ms and 620 ms, making them less engaging compared to Denmark and Belgium.

Survey analysis:
During the survey, respondents firstly answered questions related to the data in the graphs and secondly answered declarative questions about the visualisation of the data in the graphs and their usefulness.

- Can you judge from the graphs which country was most active in fisheries in 2016? - 16 people answered 'yes', 10 'no' and 8 'don't know'.
- Which type of graph best shows changes in fishing volumes between countries? - "column chart", 21 people, 61%, "pie chart" - 10 people. 29%.
- Which type of graph best shows changes in crop yields between countries? - "Circular", 22 people, 64%, "column" 10 people, 29%.
- Respondents answered the following questions in a text box:

- Which type of graph was most clear to you? - "column", 20 people, 59%, "pie", 12 people, 35%. Respondents also indicated why this chart was best for them, 18 people indicated that it was easy to read the data from it (column chart), 11 you can clearly see the differences in the overall total (pie chart).
- Which graph gives you a better understanding of the proportions? - "column" 22 people, 64%, 12 "pie", 36%.
- Which graph is more intuitive for you? - "column", 23 people, 67%, "pie" 10 people, 29%.
- Were any of the charts confusing to you? If so, why? "Linear" 28 people, 82%, "Point" 6 people, 17%. When asked to indicate why, respondents answered that a line indicates a trend or change over time that relates to one issue versus many countries, and the least visibility and understanding for a point chart.

5. Discussion

The analysis of the charts based on heatmaps and user behaviour data allows an in-depth assessment of the effectiveness of data visualisation through the charts presented in the study. The conclusions of the analysis show diversity in the ways users interact with the charts, highlighting the importance of adapting the presentation to the characteristics of the data presented. Each form of visualisation (bar, line, pie, point) played a different role, influencing the way the results were interpreted.

In the case of the bar charts, the title was the element that quickly attracted attention, as shown by the low TTFF values - but it should be noted that it is the title that can be the key explanation of the topic covered. Titles generated significant return rates of 4.5 and 6.6 respectively, demonstrating their importance in introducing users to the data topic. The figures on the vertical axis, on the other hand, were a key point of analysis, engaging users for an average of 1,600 ms in one case and as long as 2,520 ms in another.

This is due to the fact that they were the only data height information for a specific country The high return rates (7 and 5.4) confirm that the figures were the foundation of the interpretation - at the same time, it can be inferred that the researchers had to check the value for a particular country on the data axis multiple times. The bars representing countries such as Denmark and the Netherlands, which generated the most engagement, are also particularly noteworthy.

For example, the Denmark post attracted the attention of 32 users for an average of 140 ms, and the description of this country was noticed by 30 people for an average of 200 ms. In contrast, the Netherlands' post was analysed for 440 ms, making it one of the most engaging elements. Other countries, such as Finland and Portugal, were less engaging, indicating differences in the reception of visuals depending on the content presented.

Line graphs, due to their form, allowed for a better understanding of trends. The analysis showed that the trend line was the focal point of users' attention. It attracted attention for an average of 4160 ms in one example, making it the most engaging element of the visualisation. The figures on the vertical axis played a key role in the interpretation of the trends, engaging users for an average of 2190 ms and 4510 ms in the different analyses, with return rates of 3 and 6.2.

There was also a noticeable difference in interest in the points representing countries. Denmark's points had the highest engagement (1040 ms in one example), which may be due to the clarity of the data presented. The points of Finland, Belgium and Estonia generated moderate interest, with viewing times of 740 ms, 660 ms and 560 ms respectively, indicating their lower weight in the overall analysis.

Pie charts, being a more synthetic form of visualisation, attracted attention to the main part of the chart - the circle. In the analyses, the main part of the graph was analysed for 3360 ms in one example and as much as 3430 ms in another. The high return rates of 8.6 and 5.17 confirm that users focused on this part as the key element. Figures for countries such as Finland and Denmark were analysed for an average of 450 ms and 570 ms, indicating their higher engagement compared to the country descriptions. For example, country descriptions such as Portugal and Sweden generated shorter viewing times of 310 ms and 600 ms, suggesting that users appreciated the visual elements of the chart more than the textual details.

The dot plots were distinguished by more diffuse user attention, which was evident in the different analysis times of the individual dots. Titles attracted attention quickly, with the shortest TTFF of 1250 ms and 5890 ms, but were also viewed for a shorter time compared to the vertical axis figures, which generated engagement for an average of 2830 ms in one case. The points representing the countries differed in terms of attracting attention. Denmark and Belgium were the most attention-grabbing, analysed for 1040 ms and 660 ms respectively. The points of Slovenia and Estonia were less engaging, suggesting that these countries' data were less important in the overall context of the visualisation.

The survey results were also taken into account during the study, which provided valuable information on users' perception of the graphs. Analysis of the responses indicated that the majority of participants were able to identify the most active countries in fisheries from the charts, but 10 people found it difficult to clearly indicate an answer and 8 were undecided. This indicates a need for more intuitive ways of presenting data for some audiences.

User preferences for chart types were clear - column charts were considered the most readable and intuitive, as confirmed by 67% of respondents. As many as 59% of respondents identified the column chart as the most readable, as it allows for easy reading of the data. In contrast, 35% of respondents appreciated the pie chart for its clear representation of differences in the overall total.

It was also interesting to note that the majority of respondents (64%) found the column chart more helpful in understanding proportions, while the pie chart was preferred by 36%. Participants had the most problems interpreting line graphs (82% identified them as confusing), arguing that the difficulties stemmed from interpreting the trend as a change affecting one country rather than a group of countries.

6. Conclusions

Analysis of the results for the different types of charts showed varying levels of user engagement depending on their design and the data presented. The comparison of bar charts, line charts, pie charts and dot charts allows the identification of their strengths and weaknesses and the specific features that affect the effectiveness of the visualisation.

Comparison of engaging elements: Bar charts stood out as particularly engaging for users in relation to the title and vertical axis figures. The vertical axis figures, for example, captured users' attention for an average of 2520 ms, highlighting their importance as a reference point for interpreting the data. Line graphs, on the other hand, allowed users to better understand trends, drawing attention to the trend line for longer - as long as 4160 ms.

Pie charts, due to their synthetic nature, engaged users with the main part of the visualisation (the circle) for an average of 3430 ms, indicating their intuitiveness for percentage or share comparisons. In the case of dot charts, the points representing the countries with the highest values (e.g., Denmark, Belgium) attracted the most attention, suggesting that users were primarily paying attention to the dominant data.

Application according to needs: Bar charts are most appropriate when the aim is to present the data in a simple, readable way with a clear breakdown by category. For example, in the analyses of fish catches in 2016, bars representing Denmark and the Netherlands generated the highest engagement (140 ms and 440 ms respectively), indicating the effectiveness of this form of visualisation for presenting differences between values. For trend analyses, line graphs prove more effective as users quickly identify changes over time or differences between countries - the trend line was the focal point of attention in all line graph analyses.

Differences in the involvement of descriptions and figures: Numerical data on the vertical axes in all chart types took longer for users to analyse than axis or country descriptions. For example, in the case of dot charts, vertical axis numerical data attracted attention for an average of 2830 ms, while axis descriptions were analysed for only 180 ms. Pie charts, on the other hand, despite their intuitiveness, showed less interest in detailed country descriptions - analysis times ranged from 110 ms (Belgium) to 240 ms (Denmark) on average, suggesting that users preferred direct numerical or graphical information.

Country comparison: The country data in the different visualisations showed that countries such as Denmark and Belgium generated the highest user engagement, regardless of the form of the graph. In dot charts, for example, Denmark's point was analysed for an average of 1040 ms, while other countries such as Estonia and Slovenia generated analysis times of 560 ms and 620 ms respectively. Line graphs also showed more interest in the points of Denmark and Belgium, which may be due to their clear dominance in the data presented.

Practical conclusions: the analysis showed that the right choice of visualisation form for the type of data is key to increasing user engagement and facilitating interpretation. Line and bar charts work best for presenting numerical data and trends, while pie charts are more intuitive for analysing percentages or breakdowns. In future visualisations, it is worthwhile to increase the integration of textual and graphical elements, which can further enhance user engagement in analysing less intuitive charts such as dot plots. It is also important to consider the variety of forms of visualisation, as different types of data require different ways of representation.

Analysis of the results from the survey provides valuable context for the perception of the different types of charts. Column charts clearly dominated most of the evaluation categories, both in terms of readability, intuitiveness and ability to convey proportions. This is consistent with the quantitative data, which indicated that users took longer to analyse columnar data. At the same time, pie charts were highly valued by respondents for their ability to visualise differences in overall totals, making them more suitable for share or proportion analyses.

An interesting finding from the survey is the clear rejection of line charts as a tool for analysing multiple countries at the same time - their perception was confusing for 82% of respondents, confirming that they are more suitable for temporal data than comparative data. Scoring charts also failed to gain much approval, mainly due to the difficulty in interpreting them and their low readability.

A comparison of the survey results with the heat map analysis showed that users' preferences for intuitiveness and readability of the charts coincide with the temporal data and the number of interactions. For example, column and pie data attracted the most attention, which coincides with the high rating of these charts in the survey. The results point to the need to design visualisations that better address user needs, especially for more complex charts such as line and dot plots.

References:

Badenes-Rocha, A., Bigne, E., Ruiz, C. 2021. Impact of cause-related marketing on consumer advocacy and cause participation: A causal model based on self-reports and eye-tracking measures. Psychol Mark mar., 21590. https://doi.org/10.1002/mar.21590.

Białowąs, S. (Ed.). 2021. Experimental design and biometric research. Toward innovations, 1st ed. Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu. https://doi.org/10.18559/978-83-8211-079-1.

Bondarenko, O.V., Hanchuk, O.V., Pakhomova, O.V., Tsutsunashvili, G., Zagórski, A. 2022. Visualization of demographic statistical data. IOP Conf. Ser.: Earth Environ. Sci., 1049, 012076. https://doi.org/10.1088/1755-1315/1049/1/012076.

Borawska, A., Mateja, A. 2024. Unveiling the User Experience: A Synthesis of Cognitive Neuroscience Methods in Digital Product Design, in: Rodrigues Da Silva, A., Mira Da Silva, M., Estima, J., Barry, C., Lang, M., Linger, H., Schneider, C. (Eds.), Advances in Information Systems Development, Lecture Notes in Information Systems and Organisation. Springer Nature Switzerland, Cham, pp. 199-218. https://doi.org/10.1007/978-3-031-57189-3_10.

Brewer, C.A. 1994. Guidelines for use of the perceptual dimensions of color for mapping and visualization. Presented at the Color hard copy and graphic arts III, SPIE, pp. 54-63.

Cairo, A. 2013. The functional art: an introduction to information graphics and visualization. New Riders, Berkeley, California.

Chen, J., Bian, L., kumar, A., Neware, R. 2022. A research based on application of dimension reduction technology in data visualization using machine learning. Int J Syst Assur Eng Manag, 13, 291-297. https://doi.org/10.1007/s13198-021-01401-7.

Cho, H., Powell, D., Pichon, A., Kuhns, L.M., Garofalo, R., Schnall, R. 2019. Eye-tracking Retrospective Think-aloud as a Novel Approach for a Usability Evaluation. Int J Med Inform, 129, 366-373. https://doi.org/10.1016/j.ijmedinf.2019.07.010.

Crameri, F., Shephard, G.E., Heron, P.J. 2020. The misuse of colour in science communication. Nat Commun., 11. https://doi.org/10.1038/s41467-020-19160-7.

CSRC Content, n.d. Usability-Glossary | CSRC. https://csrc.nist.gov/glossary/term/usability.

Cyr, D., Head, M., Larios, H. 2010. Colour appeal in website design within and across cultures: A multi-method evaluation. International Journal of Human-Computer Studies, 68, 1-21. https://doi.org/10.1016/j.ijhcs.2009.08.005.

Da Silva Soares, R., Barreto, C., Sato, J.R. 2023. Perspectives in eye-tracking technology for applications in education. South African Journal of Childhood Education 13. https://doi.org/10.4102/sajce.v13i1.1204.

Danisch, S., Krumbiegel, J. 2021. Makie.jl: Flexible high-performance data visualization for Julia. JOSS 6, 3349. https://doi.org/10.21105/joss.03349.

Elavsky, F., Bennett, C., Moritz, D. 2022. How accessible is my visualization? Evaluating visualization accessibility with Chartability. Computer Graphics Forum, 41, 57-70. https://doi.org/10.1111/cgf.14522.

Evergreen, S.D. 2019. Effective data visualization: The right chart for the right data. SAGE publications.

Fairbairn, D., Hepburn, J. 2023. Eye-tracking in map use, map user and map usability research: what are we looking for? International Journal of Cartography, 9, 231-254. https://doi.org/10.1080/23729333.2023.2189064.

Few, S. 2009. Now you see it: simple visualization techniques for quantitative analysis. Analytics Press, Oakland, Calif.

Godfrey, A.J.R., Murrell, P., Sorge, V. 2018. An Accessible Interaction Model for Data Visualisation in Statistics. In: Miesenberger, K., Kouroupetroglou, G. (Eds.), Computers Helping People with Special Needs, Lecture Notes in Computer Science.

Springer International Publishing, Cham, pp. 590-597. https://doi.org/10.1007/978-3-319-94277-3_92.
Goldberg, J., Helfman, J. 2011. Eye tracking for visualization evaluation: Reading values on linear versus radial graphs. Information Visualization, 10, 182-195. https://doi.org/10.1177/1473871611406623.
Grant, R. 2018. Data visualization: Charts, maps, and interactive graphics. Chapman and Hall/CRC.
Gu, Z. 2022. Complex heatmap visualization. iMeta 1, e43. https://doi.org/10.1002/imt2.43.
Hall, R.H., Hanna, P. 2004. The impact of web page text-background colour combinations on readability, retention, aesthetics and behavioural intention. Behaviour & Information Technology, 23, 183-195. https://doi.org/10.1080/01449290410001669932.
Hartson, R., Pyla, P. 2012. The UX Book, 1st edition. ed. Elsevier Science, Erscheinungsort nicht ermittelbar.
Healy, K. 2019. Data visualization: a practical introduction. Princeton University Press, Princeton NJ Oxford.
ISO 9241-210:2010(en). Ergonomics of human-system interaction — Part 210: Human-centred design for interactive systems n.d. URL: https://www.iso.org/obp/ui/#iso:std:iso:9241:-210:ed-1:v1:en.
Joseph, A.W., Murugesh, R. 2020. Potential Eye Tracking Metrics and Indicators to Measure Cognitive Load in Human-Computer Interaction Research. JSR 64, 168-175. https://doi.org/10.37398/JSR.2020.640137.
Kalinin, A.A., Palanimalai, S., Zhu, J., Wu, W., Devraj, N., Ye, C., Ponarul, N., Husain, S.S., Dinov, I.D. 2022. SOCRAT: A Dynamic Web Toolbox for Interactive Data Processing, Analysis and Visualization. Information 13, 547. https://doi.org/10.3390/info13110547.
Kirk, A. 2019. Data visualisation: A handbook for data driven design (2nd Edition). SAGE Publications,
Kremsner, T.P., Pfeiffer, C., Weidinger, S., Stolavetz, C. 2023. How to visualize electricity consumption anomalies: The impact of chart types on triggered emotions and eye movements. e-Prime - Advances in Electrical Engineering, Electronics and Energy 5, 100202. https://doi.org/10.1016/j.prime.2023.100202.
Lübke, D., Ahrens, M., Schneider, K. 2021. Influence of diagram layout and scrolling on understandability of BPMN processes: an eye tracking experiment with BPMN diagrams. Inf Technol Manag, 22, 99-131. https://doi.org/10.1007/s10799-021-00327-7.
Luo, X., Yuan, Y., Zhang, K., Xia, J., Zhou, Z., Chang, L., Gu, T. 2019. Enhancing statistical charts: toward better data visualization and analysis. Journal of Visualization 22, 819-832.
Madsen, M., 2024. (Un)certain and (ir)regular futures: graph chart visualizations of forecasting in higher education. Discourse: Studies in the Cultural Politics of Education 1-17. https://doi.org/10.1080/01596306.2024.2393771.
Marques Santos, A., Conte, A., Ojala, T., Meyer, N., Kostarakos, I., Santoleri, P., Shevtsova, Y., de Quinto, A., Molica, F., Lalanne, M. 2023. Territorial Economic Data viewer: A data integration and visualization tool (Working Paper No. 04/2023). JRC Working Papers on Territorial Modelling and Analysis.
Mateja, A. 2023. Usability research of an online store using eye tracking: a comparison of product specification formats. Procedia Computer Science, 27th International Conference on Knowledge Based and Intelligent Information and Engineering Sytems (KES 2023)225, 3233-3242. https://doi.org/10.1016/j.procs.2023.10.317.

Mauri, M., Rancati, G., Gaggioli, A., Riva, G. 2021. Applying Implicit Association Test Techniques and Facial Expression Analyses in the Comparative Evaluation of Website User Experience. Front. Psychol., 12. https://doi.org/10.3389/fpsyg.2021.674159.

Midway, S.R. 2020. Principles of Effective Data Visualization. PATTER 1. https://doi.org/10.1016/j.patter.2020.100141.

Munzner, T. 2014. Visualization analysis and design. CRC press.

Nærland, T.U., Engebretsen, M. 2023. Towards a critical understanding of data visualisation in democracy: a deliberative systems approach. Information, Communication & Society, 26, 637-655. https://doi.org/10.1080/1369118X.2021.1968922.

Nash, K., Trott, V., Allen, W. 2022. The politics of data visualisation and policy making. Convergence: The International Journal of Research into New Media Technologies, 28, 3-12. https://doi.org/10.1177/13548565221079156.

Nielsen, J. 1993. Usability Engineering. Elsevier. https://doi.org/10.1016/C2009-0-21512-1.

Norman, D.A. 2013. The design of everyday things, Rev. and expanded edition. ed. MIT press, Cambridge, Mass.

Novák, J.Š., Masner, J., Benda, P., Šimek, P., Merunka, V. 2024. Eye Tracking, Usability, and User Experience: A Systematic Review. International Journal of Human–Computer Interaction 40, 4484-4500. https://doi.org/10.1080/10447318.2023.2221600.

O'Donoghue, S.I. 2021. Grand Challenges in Bioinformatics Data Visualization. Front. Bioinform, 1, 669186. https://doi.org/10.3389/fbinf.2021.669186.

Pedersen, M. 2007. Importance of region-of-interest on image difference metrics.

Poole, A., Ball, L.J. 2005. Eye Tracking in Human-Computer Interaction and Usability Research: Current Status and Future Prospects.

Riffe, T., Sander, N., Kluesener, S. 2021. Editorial to the Special Issue on Demographic Data Visualization: Getting the point across – Reaching the potential of demographic data visualization. DemRes, 44, 865-878. https://doi.org/10.4054/DemRes.2021.44.36.

Rui, Z., Chang, D., Gu, Z. 2023. Event-related potential and oscillatory cortical activities of artistic methodology in information visualization design in human–computer interface. International Journal of Human-Computer Studies, 177, 103066. https://doi.org/10.1016/j.ijhcs.2023.103066.

Scheuer, L., Torous, J. 2022. Usable Data Visualization for Digital Biomarkers: An Analysis of Usability, Data Sharing, and Clinician Contact. Digital Biomarkers, 6, 98-106. https://doi.org/10.1159/000525888.

Schloss, K.B., Palmer, S.E. 2011. Aesthetic response to color combinations: preference, harmony, and similarity. Atten Percept Psychophys, 73, 551-571. https://doi.org/10.3758/s13414-010-0027-0.

Spence, I. 1990. Visual psychophysics of simple graphical elements. Journal of Experimental Psychology: Human Perception and Performance, 16, 683-692. https://doi.org/10.1037/0096-1523.16.4.683.

Statistics - Fishery | Eurostat, n.d. https://ec.europa.eu/eurostat/databrowser/view/fish_ca_main/default/table?lang=en.

Statistics - Grain | Eurostat, n.d. https://ec.europa.eu/eurostat/databrowser/view/apro_cpsh1/default/table?lang=en.

Stone, M. 2016. A Field Guide to Digital Color, 1st ed. ed. Chapman and Hall/CRC, Florida.

Tufte, E.R. 2018. The visual display of quantitative information, Second edition, tenth edition, Graphics Press, Cheshire, Conn.

Vande Moere, A., Tomitsch, M., Wimmer, C., Christoph, B., Grechenig, T. 2012. Evaluating the Effect of Style in Information Visualization. IEEE Trans. Visual. Comput. Graphics, 18, 2739-2748. https://doi.org/10.1109/TVCG.2012.221.

Vasseur, A., Léger, P.M., Senecal, S. 2019. Eye-tracking for IS Research: A Literature Review., Proceedings of the Eighteenth Annual Pre-ICIS Workshop on HCI Research in MIS, Munich, Germany, December 15, 2019.

Wang, Y., Huang, H., Rudin, C., Shaposhnik, Y. 2021. Understanding how dimension reduction tools work: an empirical approach to deciphering t-SNE, UMAP, TriMAP, and PaCMAP for data visualization. J of Machine Learning Research, 22, 1-73.

Ware, C. 2019. Information Visualization: Perception for Design. Morgan Kaufmann.

Waskom, M. 2021. seaborn: statistical data visualization. https://doi.org/10.21105/joss.03021.

Zeng, L. 2009. Designing the User Interface: Strategies for Effective Human-Computer Interaction by B. Shneiderman, C. Plaisant: Pearson Addison-Wesley, xviii+ 606 pages. ISBN: 978-0-321-53735-5.

Zong, J., Lee, C., Lundgard, A., Jang, J., Hajas, D., Satyanarayan, A. 2022. Rich Screen Reader Experiences for Accessible Data Visualization.