



BACHELOR THESIS

Do different data visualisation forms of
corona data cause a difference in people's
assessment of their health risks?

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Abstract

This research analyses the influence of different Corona-visualisations on people's health risk assessment. Therefore six different visualisations, two visualisations of three different chart families each are analysed. The individual visualisations are compared within their families and the families between each other. They are primarily tested on the influence of different colour shares and time axis. It is anticipated that visualisations that contain a colour share with much green and little red as well as a continuous time axis lower the perceived health risks. The data base for this research comes from a survey (May 2021) with 112 cases that presented all visualisations in a within-subject design to the participants. All six visualisations were representations of the same Corona-data. The sample consist of mostly young well educated people. The findings suggest that the differences between the visualisations within the families are mostly significant and as expected. The influences of the different families are also significant and in line with the hypotheses. The families of Categorical and Hierarchical Charts do not influence the health risk assessment. The family of Temporal Charts lower the health risk assessment level. The interaction between form and content of the visualisations stands out as an underestimated role.

1. Background

The effects of data visualisation are discussed in almost all fields of science. To know these effects is necessary to understand and use the fast-developing science of data visualisation. Especially in politics and administration, the techniques of data visualisation are aspiring fast to a relevant factor. Although there is already much knowledge, there is still much to research in this relatively new field (Friendly 2008). At least since the year 2020 and the beginning of the then-new COVID-19 virus, data visualisation and its connection to politics became aware to all people. Since then, a daily release of current data has accompanied the pandemic. These visualisations helped the politicians make health-protecting decisions and the public to understand these decisions and the whole situation better.

This seems to be a pretty new phenomenon. Looking back to the past decades of policies, particularly on environmental protection policies, communication via data visualisation would have been possible. It would still be possible to use the available data to visualise the necessity of environmental protection policies and communicate them to the public. However, there has been at least a little use of data visualisations in this context, but mainly as a political-administrative steering tool. One example would be the United Nations Framework Convention on Climate Change (UNFCCC) to set its climate policy goals (Nærland, 2020).

Nevertheless, a spread of data visualisation to the public in a dimension that happens currently with Corona-data never happened before. The present time shows that a lot of people use the in the Corona context presented data to evaluate their personal health risk continuously. The public seems ready to deal with data visualisation as a communication form. If this experience leads to a cross-thematic data visualisation application, once Corona is not the dominant topic anymore, is to be seen.

However, Corona has led to the fact that data visualisations created by administrations, as a form of communication, are used to a hitherto unknown extent. This has some implications that can be seen as a motivation for this research. Data visualisations are associated with objectivity and truthfulness (Masson & van Es, 2017). These criteria make them seem trustworthy (Kennedy et al., 2020). This makes them a welcome

information source for many people and explains why they are widely used. But these associations with objectivity, truthfulness and their possible consequence, the assumed trustworthiness, are not true without restrictions. There are a lot of decisions and trade-offs involved in the creation of data visualisations. This means that there is more than one mathematical correct visualisation of the same data. How the different data visualisations of the same data influence the recipients is a question that needs to be researched.

Many aspects could have been researched, the scaling of the visualisation, the title used, or the interactivity. These are all things that have a possible influence on the perception of the data. Nevertheless, the choice of the research subject fell on a, in the design process chronological more early aspect, the type of the Chart. There are uncountable numbers of different chart types that have specifications in all directions. They are meant to support the recipient in perceiving the data. If they, at the same time influence the already mentioned individually perceived health risk of the recipient is the focus of this research. This is examined because the individually perceived health risk is the information that people continually try to extract from Corona-visualisations. To see whether the perceived information (namely the health risk) depends on the visualisation of that information is crucial for the future handling of visualisations. Although this seems to be a simple research occasion, the theoretical background is relatively unexplored. Most research focuses on specific aspects of visualisations and not the visualisation form itself. If and how the knowledge derived from this previous research can be transferred to this research will be discussed.

The social relevance and the scientific relevance of this question comes from multiple aspects. In general, it is understandable that technologies that enter a certain position where they reach a broad audience, as data visualisation has done by now, should be checked for potential threats. Especially a technology that most people see as an objective one has a substantial possible impact on influencing people. A specific concern arises from the fact, that people after perceiving a Corona-visualisation, could adapt their actions to the individual health risks taken from the graph. This would mean that if the graph type distorts the perception of individual health risks, people will not

behave according to the actual risks. If a technology as data visualisation was used without knowing its different application's consequences, the results could be massive. The trust in the ones deploying that technology and the trust in the technology itself could be harmed or at least questioned. Therefore it is essential to identify possible influences the technology has and evaluate how to handle them responsibly. To not lose this trust should be seen as a motivation to research this topic.

This helps to fill the scientific knowledge gap that occurs because most visualisation research focusses on individual components of visualizations and researches them separately. This results in a underestimation the of the influence the visualisation forms itself could have. To explore the effects of the different forms in connection with the individual components of visualizations is the scientific knowledge gap that will be filled.

To meet the relevance of this topic, it is necessary to approach this topic systematically. The research aims to better understand how different data visualisations forms, to be more detailed, different graphical presentations of the same data, influence people and their health assessment. The Corona-pandemic delivers the option to research this while people are in daily contact with data visualisations. Therefore the research will focus on how different Corona-data-visualisations influence people and their health assessment. To research this a research question:

Do different data visualisation forms of Corona-data cause a difference in people's assessment of their health risks?

is formulated. To have a more detailed approach, a focus on different chart families will be set. An insight into the different chart families and the different visualisations will be provided in the following theory section. To generally compare them, the following more specific formulation is developed :

Does the usage of different chart families affect people's assessment of their health risks?

A comparison of visualisation forms within the chart families reveals the following three sub-questions:

Does the usage of Bullet Charts versus Heat Maps in Corona-data-visualisations affect people's assessment of their health risks?

Does the usage of Waffle Charts versus Stacked Bar Charts in Corona-data-visualisations affect people's assessment of their health risks?

Does the usage of Line Charts versus Stacked Area Charts in Corona-data-visualisations affect people's assessment of their health risks?

The theory chapter will clarify the choice of the six different chart types and explain why there are expectations that the different forms affect people's assessment of their health risk. It also gives a detailed insight into the chart families and explains what influence the different graphs could have. The third chapter will then explain how a survey was used to answer this question. A careful analysis of the collected data will be made after the data is presented and explained (Chapter 4). The last chapter will draw a conclusion (Chapter 5).

2. Theory

The history of data visualisation with all its different phases and its different ideas has led to various visualisation forms. The traditional forms, as Li (2020) describes them, are a good background before dealing with them and analysing if they can influence people (Li, 2020). They help to approach the theoretical background that has the following setup.

First, a general understanding of data visualisation will be provided. Within the boundaries of this definition, a second paragraph will explain how the broad diversity of different data visualisations is narrowed down to a smaller category of researchable forms. Out of this category, a small number is chosen to compare and analyse them; this happens in a third paragraph. A fourth paragraph will study if data visualisations can influence people, especially their personal health risk assessment. A fifth

paragraph then will develop hypotheses that are based on the already gathered knowledge. These hypotheses should predict how the different visualisations influence the recipient's health assessments. The last paragraph will look at the possible theoretical limitations of this research.

2.1. Definitions

First, a general understanding of data visualisation is needed.

Most definitions focus on "visual representation of data" and state that it is the central aspect to reveal patterns in the data (Li, 2020). Data, in general, is the term for "raw, unprocessed information that is not recognised as having any meaning" (Li, 2020). Li states that "Central to the process of data visualisation is the transformation of data into information." (Li, 2020).

The following necessary distinction is the division of data visualisation into information visualisation and scientific visualisation, even though they are very similar.

Information visualisation is "the process of representing abstract data in a visual way, which users can understand meaning of it" primarily it arises in the form of Tables, Charts, Trees, Maps, Scatter-plot, Diagrams and Graphs (Li, 2020).

Scientific visualisation is "the representation of data graphically as a means of obtaining comprehension and insight into the scientific data", Simulations, Waveforms and Volumes are its typical forms. Because the main interest of this research is connected to the during Corona frequently used graphics, a focus on information visualisations is set.

2.2. Often used visualisations

To get a feeling of which forms should be researched, it is necessary to know what forms are most commonly used during the Corona-pandemic. The choice should fall on a form that users are generally comfortable with, so the viewers are not overwhelmed with the visualisation's theoretical concept. Therefore research that analyses the most used data visualisation forms is helpful.

A first idea which forms this are can be found in the research by Trajkova et al. (2020). This research analyses which forms of data visualisation is most used on Twitter in the context of Corona-data. Although Twitter is not representative of the whole population,

this is a first good insight. The findings of this research can be concluded as followed. "Regardless of generation (organisations vs. individuals), visualisations that include temporal series, such as line graphs and bar graphs, are those that get most frequently retweeted." (Trajkova et al., 2020). Therefore a focus on information visualisations that show a temporal series seems legitimate.

Another study focusing on seven major daily newspapers in Korea delivers a more detailed picture of the usage of different data visualisation forms. Out of the 5924 analysed news stories published on the same and the following day of six chosen critical COVID-19 events, 2491 were COVID-19 related. 160 of these stories used one or more graphs. In total, there were 232 graphs; they were divided into ten different graph types. 37.5% of these graphs were line graphs, 32.3% bar graphs. The third most used visualisation form is a table (10%). These three types together reach more than 80% of all Corona-visualisation in the analysed time. All other graph types did not reach more than 10% each. (Kwon et al., 2021)

A third study by Lee et al. (2021) has similar findings. In their data set, they found "Line Charts (890 visualisations, 21% of the corpus), area charts (2212, 5%), bar chart (3939, 9%), pie charts (1120, 3%), tables (4496, 11%), maps (5182, 13% dashboards (2472, 6%), and images (7,128, 17%)" (Lee et al., 2021). They analysed a "dataset, which included over 390M tweets spanning January 21, 2020–July 31, 2020" (Lee et al. 2021).

2.3. Visualisations to be studied

To finally select some forms that will be researched, a closer distinction of the visualisations forms is necessary. Andy Kirk divided multiple visualisation forms into families that get distinguished by their primary role. Out of these five families of chart types, only three are relevant because of their primary role. These three families are categorical, hierarchical and temporal charts. The other two families are Relational and Spatial charts. The first focuses on correlations, and the second on overlays and distortions. Both families are not compatible with the just established restrictions. The spatial family does not include time series (as long as it is non-interactive). The relational family focuses on correlation which is uninteresting in the context of classic Corona-visualisations. Within each of the three remaining categories, two visualisation

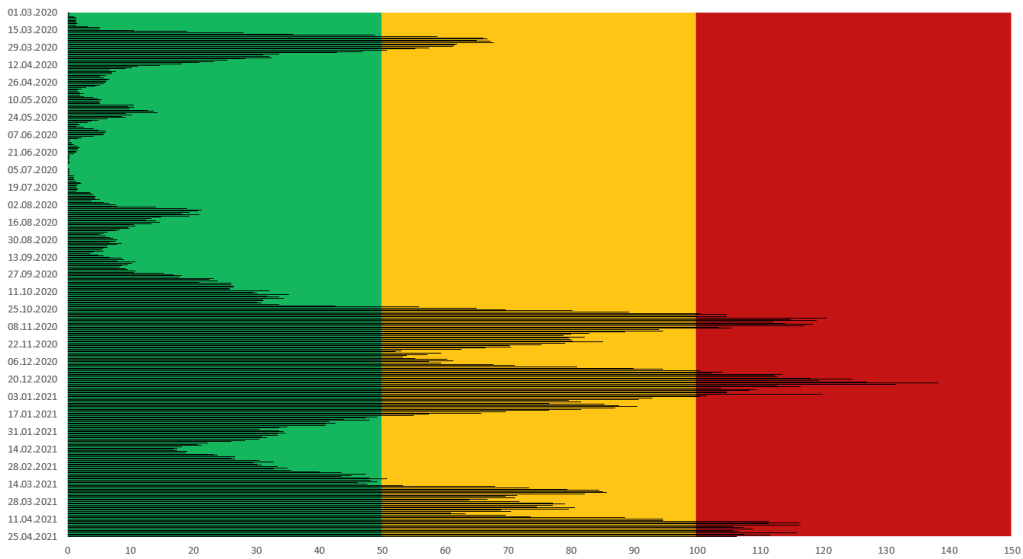
forms will be selected to have a reasonable amount of graphs to compare. The ones that fit the established limitations best are the preferred ones. Therefore the display of a time series is necessary, and an assignment to the frequently used categories is desirable.

The now presented visualisations are structured by their categories. The individual visualisations were all created in excel with official the then up-to-date data for the city Münster in Germany (Landeszentrum Gesundheit Nordrhein Westfalen: 2021).

Categorical charts have the primary role of "comparing categories and distributions of quantitative values" (Kirk, 2019). Two charts out of this category that focus on time courses and comparison are Bullet Charts and Heat Maps. These two graphs are specialised in comparing data. The Bullet Chart also is a graph that belongs to the category of often used graphs during the Corona-pandemic. (Kwon et al., 2021)

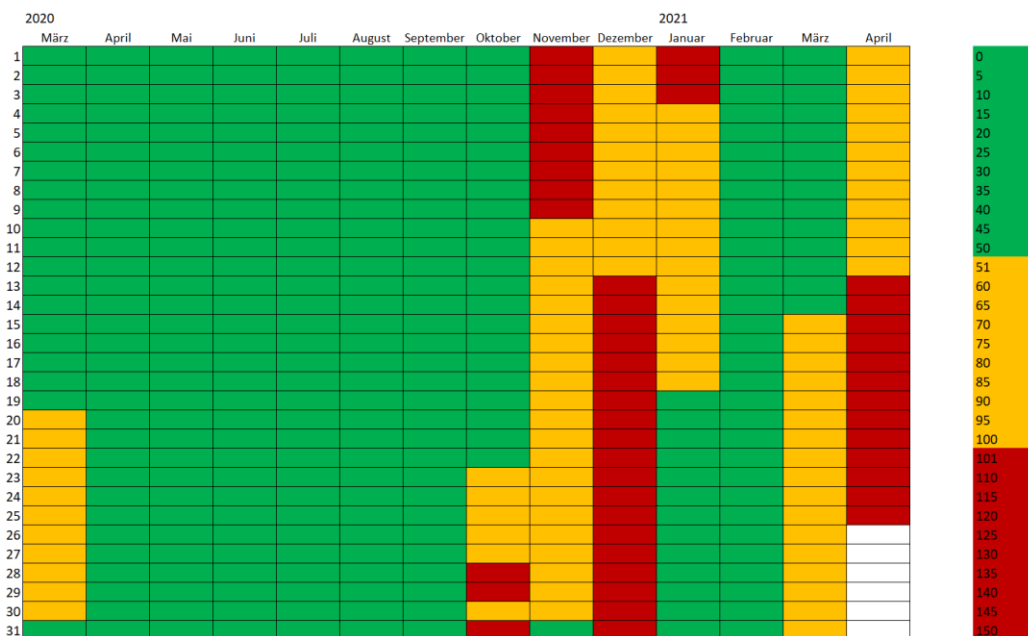
The Bullet Chart (Figure 1) "is effectively a bar chart displaying quantitative values for different categories, but incorporating additional bandings to assist with interpreting the bars" (Kirk, 2019). The graph consists of bars, where their length represents a quantitative value for each element. Often a colour attribute is used to distinguish value areas behind all bars to facilitate interpretation. (Kirk, 2019) In the presented list, the Bullet Chart is the only visualisation that provides the information of the actual 7-day-incidence, all other graphs either show the incidence category of each day, the share of 7-day-incidence categories within a month or the total ratio of all 7-day-incidence categories over the whole time.

Figure 1: Bullet Chart



The Heat Map (Figure 2), sometimes also called a table chart, "displays quantitative values across the intersections of two categorical and/or discrete quantitative dimensions" (Kirk, 2019). The Chart includes two axes with different values that create a tabular layout. The assigned cells differ in colour to represent the related quantitative value. Classically, the axes are month and days, making each cell a specific date with a different colour depending on its assigned value. (Kirk, 2019)

Figure 2: Heat Map

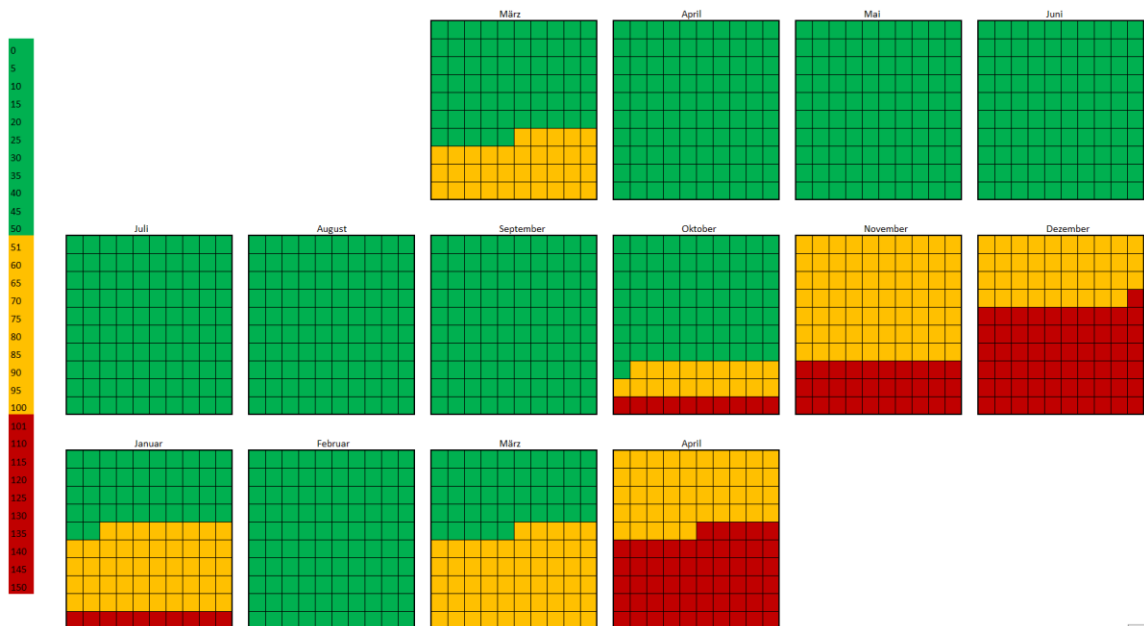


Although both these graph types are from the same family, they still have differences. The Bullet Chart allows recipients a more detailed analysis of their own health risks. It is possible to differentiate within the categories. While the Heat Map suggests that all "green days" were the same, a day with a peak within the green category in the Bullet Chart could already cause concern.

Hierarchical charts are designed for "revealing part-to-whole relationships and hierarchies" (Kirk, 2019). Part-to-whole visualising charts are preferred over hierarchy visualising charts because hierarchy charts often fail to include time series. Two charts out of this category that focus on time developments and part-to-whole visualisation are the Waffle Charts and the Stacked Bar Charts. The Stacked Bar Chart is a variant of the during the Corona-pandemic often used bar chart.

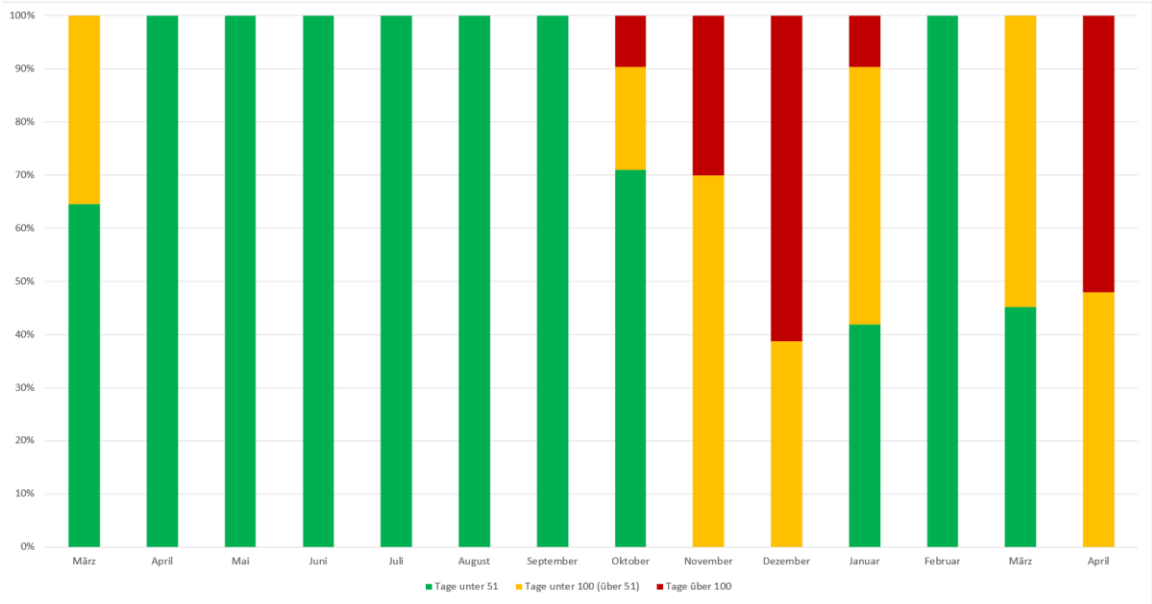
The Waffle Chart (Figure 3) "shows how proportions of quantities for different constituent categories make up a whole" (Kirk, 2019). When displaying time series, it divides time periods into 100 cells in a grid layout. These cells then show the proportions in this time period by having different colours. (Kirk, 2019)

Figure 3: Waffle Chart



The Stacked Bar Chart (Figure 4) visualises "how quantitative values for different constituent categories make up a whole across major category items" (Kirk, 2019). When Stacked Bar Charts include a time series, they "show how value proportions have changed over time" (Kirk, 2019). Each bar then represents a specific time period and shows the proportions in this time period.

Figure 4: Stacked Bar Chart

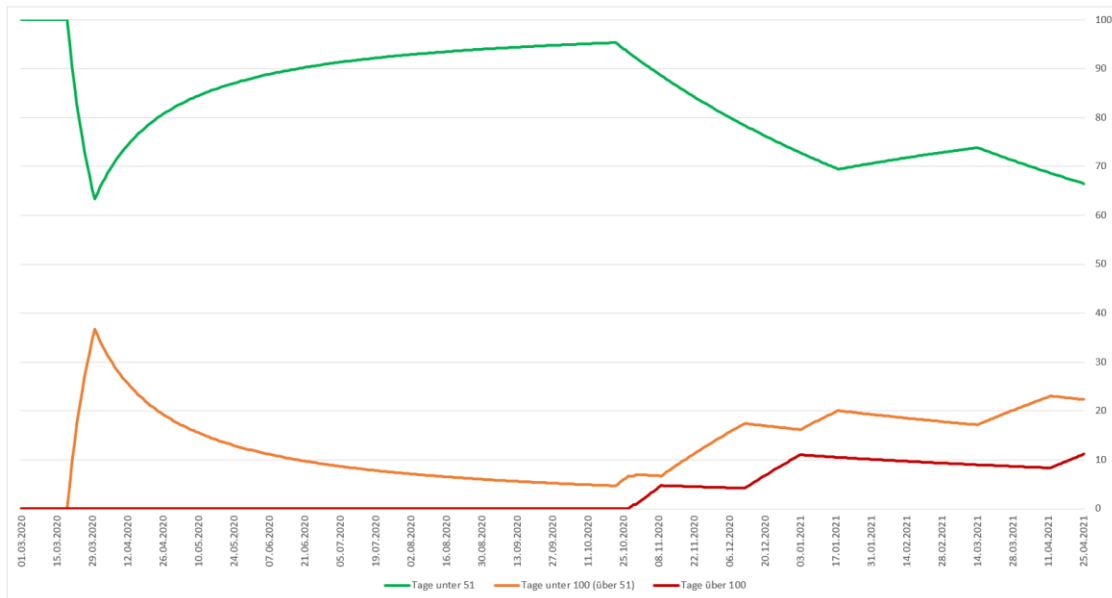


So both visualisation forms show the same proportion of colour, and both show the share of the three categories split up by month. Even within the month, there is no chronological order but order by category. This however it is not obvious, that these visualisations have any differences that are relevant for a different health risk perception. A comparison however is still useful, because it gives a good opportunity to see if and how different forms influence when they characteristics of are very similar.

Temporal charts are designed for "plotting trends and intervals over time" (Kirk, 2019). Trend visualising charts are preferred over other chart types of this family because a time series is more easily includable, and they are closer to the during the Corona-pandemic frequently used graphs. Two charts out of this category that focus on time courses and trend visualisation are Line Charts and Stacked Area Charts. The Line Chart is an often used graph during the Corona-pandemic (Kwon et al., 2021).

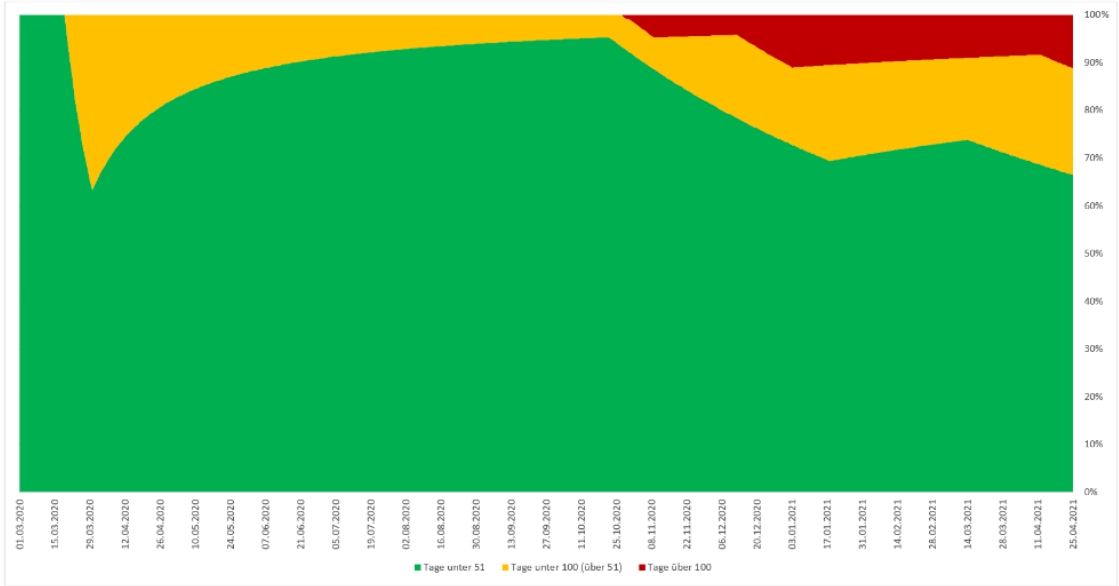
The Line Chart (Figure 5) visualises "how quantitative values have changed over time for different categorical items" (Kirk, 2019). Line Charts often contain an x-axis that displays a time series and a quantitative y-axis. Then multiple lines visualise the value of different categories over time. Also, the visualisation of proportions in the categories is possible.

Figure 5: Line Chart



The Stacked Area Chart (Figure 6) visualises "how quantitative values have changed over time for multiple categorical items" (Kirk, 2019). They usually contain an x-axis that displays a time series and a quantitative y-axis. "To accentuate the shape of the trends, the area beneath the line is filled with colour, which means the height of the area at any given point also reveals its quantity" (Kirk, 2019).

Figure 6: Stacked Area Chart



Accordingly, both visualisations show the cumulative percentage of 7-day-incidences on each day for the entire previous period. Thus, in order to assess personal health risks over a period of time, only one point in the graph needs to be looked at. The difference is that the Stacked Area Chart stacks the different categories. The Line Chart enables the recipient to find out more easily the value the lines reach each day. While with the Stacked Area Chart, the recipients have to do simple subtractions to get the same information. Additionally, the Stacked Area Chart fills the area under the lines and therefore uses more colour.

One aspect that should be shortly discussed, is the interaction between form and content. This means that the findings in this research are dependent on the used dataset. The influence of the colour for example will be mainly explained over the share of colour in the individual visualisations, this share is nearly the same in almost all visualisations that use much colour.

However the general colour share in all visualisations is dominated by the colour green. The Stacked Area Chart has a higher amount of green (83%) and lower shares of red (3%) and orange (13%) in contrast to the other three visualisations that use a lot of colour (Heat Map, Waffle Chart, Stacked Bar Chart), which can be explained with its cumulative approach. In all of the other three visualisations about 66% were green, circa 12% of the visualisations were red and 22% orange.

2.4. How visualisation influence perceptions

To see the advantages and disadvantages of the different visualisation forms, they will be compared in their families and the families among each other.

The comparison might show differences in how strong the visualisation forms influence people. Where these influences come from, and if the choice of a data visualisation really can influence people or even cause a difference in people's attitudes shall be discussed next. A first literature review suggests that "Emotions are vital components for understanding the social world, including data visualisations." (Engebretsen & Kennedy, 2020). To get a deeper understanding of emotions and the link to data visualisation, the view of a broader context, the data arise from is necessary. "Emotions are evoked by data themselves, subject matter, the locations in which data are encountered and by people's sense of their own abilities to make sense of and engage with data." (Kennedy & Hill, 2018). This implies that different data visualisation forms have different effects on the visualisation perceiving persons. But where does this effect come from, and what does that mean for the chosen visualisation forms?

A first focus should be set on what role data visualisations play in attitude change in general before looking at the effects on health assessment. Research done by Herring et al. (2016) focusing on data visualisation in climate change has the following findings. "all participants scored strong changes in beliefs and attitudes as a result of interacting with the site" (Herring et al., 2016). They researched the effects of people using an

"interactive map-based climate visualisation that public web users could use to search for their local areas of interest and see the differences between emission scenarios" (Herring et al., 2016). These findings can have more reasons than the simple use of data visualisation. Research, if "interactivity itself as a variable influences beliefs and attitudes" is necessary (Herring et al., 2016). However, this proves that data visualisations can change people's attitudes. A focus on non-interactive data visualisations and how they can help to decide if behaviour change is reasonable can be found in the research of Christmann et al. (2017). This research states that the "reflective stage, which is crucial for behaviour change, can be facilitated with suitable visualisations that allow users to answer specific questions with regard to their health data." (Christmann et al., 2017). This then should help the individuals to improve their behaviour. However, they find that using point charts and accumulated bar charts is not ideal for identifying correlation but suggests using a traffic light system combined with a point chart. This second example shows that data visualisations can influence people and change their attitude and possibly even their health assessment. A transfer of this to the dependent variable health risk perception should result in similar findings.

Another relevant finding can be seen in the research by Ancker et al. (2006). They find that graphs that show the data on a single continuous time axis tend to communicate a lower health risk. This is because these graph forms lead the recipients to transfer the implied health risks of the data visualisation to the whole shown time range. (Ancker et al., 2006) These visualisation forms suggest that the risk spreads over the whole time axis and thus reduce the perceived level of risk independently of the specific data development (e.g. the slope, general level, etc.). On the other hand, graphs with several individually visualised time periods increase the health risk assessment.

Another fitting explicit finding can be found in research on "The Visual Communication of Risk" by Lipkus and Hollands (1999). They conclude that "Graphs that contain a reference point (e.g. [...] colours that highlight level of risk) to indicate level of hazard threat (i.e., low, moderate, or high risk) affect risk perceptions, intentions, and possibly behaviours" (Lipkus & Hollands, 1999). Transmitted to this research, this would mean that the colour green in contrast to the colour red suggests a lower health risk and vice versa. However, this effect depends on the ratio of the colours within the individual graphics. Since green is the dominant colour in all visualisations that use colour as a

reference point, this shifts the general implied health risk of all visualisation with high colour use to the lower end of the scale.

2.5. Hypothesis

These theories lead to the assumption that different chart types influence people's assessment of their health risks differently. The question now is, what individual influence do the different chart types have?

Based on the findings by Ancker et al. (2006), that a single continuous time axis relatively lowers the perceived health risk, a first hypothesis can be formulated. The effect of the single continuous time axis is expected to primary effect three visualisation forms. The Bullet Chart, the Line Chart and the Stacked Area Chart. The specific values and development of the underlying data set therefore set a certain level of perceived health risk and this effect lowers it to a certain extent. This leads to the following hypothesis:

H1: Graphs that show the data on a continuous time axis (Bullet Chart, Line Chart, Stacked Area Chart) tend to communicate a lower health risk.

Visualisation form	Continuous-time axis	Implied health risk
Bullet Chart	Yes	-
Heat Map	No	+
Waffle Chart	No	+
Stacked Bar Chart	No	+
Line Chart	Yes	-
Stacked Area Chart	Yes	-

--: strongly decreases -: decreases, o:remains the same, +: increases, ++: strongly increases

Based on the presented findings by Lipkus and Hollands (1999), that graphs that contain a reference point to communicate the riskiness can influence the risk perception, a second hypothesis derives. The specific implementation of these reference point could be relevant. Graphs that use this reference points more strong

could imply higher or lower risks. This would be because the colours that imply a higher or lower health risk are more present. For example an increases in the share of red colour would create a higher health risk perception. However, all visualisations that use colour as a reference point have the same ratio of colours because they use the same data, except the Stacked Area Chart. The dominant colour in the general colour share over all visualisations is the colour green. (see also 2.3.) This would mean that the Bullet Chart, the Heat Map, the Waffle Chart and the Stacked Bar Chart communicate a higher health risk than the Line Chart, but still a lower level than the visualisations without much colour. This leads to the following hypothesis:

H2: Graphs that make higher use of colour as a reference point (Bullet Chart, Heat Map, Waffle Chart, Stacked Area Chart and Stacked Bar Chart) can communicate a higher or lower health risk, dependent on their used colour share.

Visualisation form	Colour share	Implied health risk
Bullet Chart	Equal colour share as background	o
Heat Map	67% green, 22% orange, 11% red	-
Waffle Chart	66% green, 22% orange, 12% red	-
Stacked Bar Chart	66% green, 23% orange, 12% red	-
Line Chart	No colour as reference point	o
Stacked Area Chart	83% green, 13% orange, 3% red	- -

- -: strongly decreases - : decreases, o:remains the same, +: increases, ++: strongly increases

These hypotheses indicate how the visualisations mentioned in the sub questions could affect the assessment of health risks. According to the analysed theory, the effects on the health assessment of these six different graphs can now be predicted. The effects of both hypotheses are therefore combined as they are equally strong.

Visualisation form	H1	H2	Combined implied health risk
Bullet Chart	-	0	-
Heat Map	+	-	0
Waffle Chart	+	-	0
Stacked Bar Chart	+	-	0
Line Chart	-	0	-
Stacked Area Chart	-	--	--

--: strongly decreases -: decreases, 0:remains the same, +: increases, ++: strongly increases

With regard to the first three sub-questions the following statements derive. They include the formulated hypotheses and the effects of the specific data that is used for all visualisations (the biggest category was green). It is anticipated that within the categories:

Heat Maps lead people to assess their health risk slightly higher than Bullet Charts.

Waffle Charts lead people to assess their health risk the same high as Stacked Bar Charts.

Stacked Area Charts lead people to assess their health risk slightly lower than Line Charts.

The sub question if different chart families affect people's assessment of their health risks can now also be predicted. The prediction of the behaviour of the individual graphs can be applied to this question and combined with the influences of the different families themselves that was already described in the theory. This gives first insights on how the different families could be ranked. The answers to the sub-question culminate in the assumption that the chart families lead people to assess their health risk differently.

The hierarchical charts lead people to assess their health risk the highest; the temporal charts lead to the lowest health risk assessment, the categorical charts come in between.

All this prediction are always related to the general level suggested by the data. The hypotheses deal exclusively with a relative shifts around this level.

2.6. Possible threats

That the findings of the analyses match, these expectations are unlikely. There are more effects from unknown variables on the measured items than here suggested. Next, the combination of the both mentioned effects as if they are the same strong is unfounded. The research, however, has the primary goal and the possibility to show that there is an effect. To explain this effect in detail is not possible within this framework.

However, if there is an effect, it is still possible that this effect is not very big. A study by Sevi et al. (2020) that researches the difference of logarithmic versus linear visualisations of COVID-19 cases does not find any effect for citizens' support for Confinement in Canada. They state that possible reasons why the treatment did not have any effect are because "Canadians have already formed strong and firm opinions on the issue [or because the] treatment did not convey any new information" (Sevi et al., 2020) because people were informed about the effect of linear and logarithmic scales. Similar effects could arise in this research and limit the findings.

Even if this research has these limits, it is still relevant to do this research because "Visualization tools are potentially too powerful either to be ignored or used without careful consideration." (Sheppard, 2005).

3. Data/documents

To answer the research question, a fitting dataset is necessary. The dataset has been collected specifically for this research. This chapter will explain how the measured concepts were operationalised (3.1.), how the general research and the survey have been designed (3.2) and how the cases for the survey have been selected and sampled (3.3). The last chapter (3.4.) describes the resulting data set.

3.1 Operationalization

Essential for this research is the conceptualisation of the concepts. The so-far formulated concepts are "perception of their personal health risks" and "different data visualisation forms". They will first be conceptualised into facets, and then to measure them adequate, they need to be operationalised into indicators.

The concept of "different data visualisation forms" will be defined by Kirk's (2019) categories, which were already mentioned in the theory part. For this research, relevant ones are again Categorical charts, Hierarchical charts and Temporal charts. These are the relevant facets of this concept. Defining these visualisation types was necessary to see if a data visualisation is located in one of these facets. If data visualisations meet these defined indicators, they are suitable for this research. Due to capacity limits, only two forms of each chart family will be used. These are the ones presented in the theory section.

The concept of "perception of the personal health risk" has many facets. Three possible facets that one could generally think of will be presented. The first one is: How afraid a person is to get ill or hurt. Another one could be: How likely the person is to survive a medical event due to underlying conditions. The next possible facet one could think of is: How good the person can protect himself against a health incident. These and potentially other facets could be observed by asking people questions about these specific aspects. These facets could be reformulated into a question a person can answer. Self-positioning on scales, as answers to the questions, would be good indicators. Alternatively, the agreement to a statement would be possible.

A literature review, however, "suggest[s] that a single question — "How risky is the situation?" — captures the concept of risk perception more accurately than the multiple-item measure" approach compared to (Ganzach et al., 2008). This is why this technique will be used in this research. A single question on how high people think the risk is for them is the indicator that will make the concept of "personal health risk perception" measurable. As the theory part has shown, data visualisation can change attitudes like this. The presented indicator will be measured after interacting with different data visualisation forms to see how the effect of different data visualisation forms on this concept is.

3.2 Research and survey design

The general research design structure of this research is based on the official regulations for the bachelor thesis and Flick's standardised research process (Flick, 2016). Combining these led to the structure that is used. This setup also has possible

threats, for example, the missing context of the collected data. Because the data collection takes place in a highly standardised setting, it lacks to capture the individual and specific context it derives from (Flick, 2016). Another threat is that planned structural observations have a problem capturing the motivations behind the observed cases' behaviour (Flick, 2016). To achieve a deeper understanding of a qualitative procedure with in-depth interviews would have been a better research design. However, since the main interest comes from verifying if an effect is generally existing and how common it is, this quantitative research design has been chosen.

The design of the survey is another important part. It is essential that it fits the whole research design and contributes to answering the research question.

In the survey the participant stated how they assess their health risks after seeing different data visualisation forms of the same data. The participants had to answer questions. The questions are intended to assess 1) Participants' impression of the data visualisation. 2) how they assess their personal health risk 3) what they think of one data visualisation compared to another. Their assessment is determined using a scale from 0 to 10. To do this, they indicate how much they agree with a statement. To answer the survey, respondents should not need longer than 10 Minutes. This has been taken into account while designing the survey. To achieve this, the number of questions was kept low. Surveys that take too long tend to suffer from attendees that stop participating. Furthermore, it is essential to note that the Corona-pandemic is a difficult situation for many people. It is anticipated that some of the participants may be sensitive to the Corona-pandemic's issues and its impact on health. Therefore, a heads-up was given that the study involves these issues, and an explanation of the shown data visualisations is provided after the study.

The study itself is designed as a survey experiment with a within subject design. In a within-subjects design, every person who takes the survey sees all visualisations, and then answers questions about each visualisation. In contrast to a between subject design this has strength and weaknesses. A strength is the reduced number of participants that is required, because each participant answers more question than in a between subject design. Another strength is that a direct comparison is collected.

Every person sees every visualisation and therefore their ratings include already the direct comparison. Each individual get every treatment and is its own control group. Due to the random order of presentation this effect is independent from the order they saw the visualisations. A weakness of the within subject design, especially in contrast to the between subject design is that a unbiased reaction only can be captured once. A participants reaction to the second visualisation is biased by the first visualisation. This however also is mitigated by presenting al visualisations in a random order. Therefore the selection of respondents has no negative influence on the validity.

A survey experiment combines benefits from laboratory and field experiments (Sniderman, 2011). Another benefit of using an survey experiment is that the aspects of causality can be achieved more easily. An experiment has the advantage of a controllable treatment; this leads to the exclusion of interfering third variables to determine whether an effect is present. The other two aspects of causality, a consequence in time and an association, can also be ensured by doing a survey experiment.

The validity of this research needs to be viewed from two sides. On the one hand, the internal validity would have been higher if a laboratory experiment was chosen. On the other hand, the external validity would have been higher in a field experiment. The survey experiment is a good trade-off between these two options. It combines them and leads to a solid general validity. The statistical conclusion validity will get a closer look once the statistical analysis has been done. The content validity can also be seen as relatively high, as argued the used question is an adequate approach to measure all relevant facets. In addition, the results are to be checked through a "ranking question". The last question will further see if the graphics were perceived as having different data.

Data collection methods are another essential part of this research. A causal hypothesis testing study is the primary selected method for data collection. As the central concept, the survey was used. The cases were selected anonymously in a cross-sectional time setting. This is a choice that happened primarily out of the context

of time resources. A longitudinal study would have given the possibility to see some developments in the researched area. Due to the limited time frame for this research, this is not possible. The quantitative data that gets collected then will be analysed.

The setup of the survey was contained a first part that collected some general data of the participants. It collected the variables: age, gender, education, current residence.

The second part of the survey showed the six different visualisations, visualizing the COVID19- Situation in Münster from March 2020 to April 2021 and asked the participant to indicate how risky the presented situation was. The scale that the answer was indicated on reached from 0 to 10. The value 0 was described as "as risky as usual". The value five was labelled with the words "slightly riskier", and the end of the scale showed the term "extremely risky". The six visualisations were presented in randomised order to prevent that the order of presentation had an influence. Also, the effect of the respondents coming back to the same question after seeing different data visualisations could make the participants think about what the different presentation of data does for their risk assessment. To avoid this, the introduction of the survey implied that each visualisation used different data. To evaluate if the participants knew that all visualisations used the same data, the last question asked the respondents to what extent they thought, that different data were used. This is another variable.

Two other collected questions focused on the comparison of the presented visualisations. The first question asked the participants to rank the visualisations by the riskiness they indicate. These results are helpful to check if they match the collected data from the first survey part, where the visualisations got individually evaluated. The second question evaluated the order in that the participants preferer the different visualisations while answering the questions from the first survey part. This helps to analyse if the preference of a visualisation influences the risk assessment. Both questions are stored as multiple variables. Each question has six variables. The six variables represent the order of the ranking the participants indicate. Every variable/position has a value that represents the visualisation that holds this position.

3.3 Case selection and sampling

The selection of cases and what kind of sampling was used is an essential step in the research process. It defines how powerful the statements of this research are and where they can be transferred to.

The population that will be analysed are over 18 years old persons that currently live in Germany. The idea behind this limitation is not to mix possible regional effects. It is imaginable that persons give different evaluations depending on their location. This might come from several effects. On the one hand, they might have contact with other forms of data visualisations depending on their current place of living. They, therefore, have different evaluations of the same visualisation.

On the other hand, an age limit was set. This was to avoid the more strict regulations when dealing with the data of minors and the more common characteristic among adults to deal reasonably with graphics. The choice to study adults living in Germany has been made to increase the available data. The field of research happens in this location because it is easy to access, and therefore more potential participants are available. The country is more easily to research because of the researchers' location.

The sampling method that was used while distributing this survey was a simple random sample. This gives all subjects in the population the same chance to be a case. The spread of the study happened in multiple areas and multiple ways. The survey was available only online. It was possible to participate via computer, tablet or mobile devices. The survey was optimised for bigger screens. Nevertheless, participation on mobile devices was adequate. The participation in the study was anonymous. Participants were addressed through social media, in-person and on survey exchange websites. The website that gathered the most participants was SurveyCircle; this is a research platform based on the principle of mutual support. Another approach that happened was personal contact. This distribution, however, was tedious, not least because of the Corona-pandemic prevailing at the time. This two way approach shall ensure that enough participants are reached and not all come from the same social group. However these ways of selecting participants were not random in terms of the research population.

This selection and sampling are suitable for the research because it allows answering the research question based on a comprehensive data set. The research question does not focus on a specific population. This limits the research because its findings are only transferable to the here selected population.

After the data collection (2021.05.22 to 2021.06.01) , a dataset with multiple variables originated. This data set will be described before the following chapter analyses the cases' values in the different variables. The dataset contains 120 variables in total, after anonymisation and cancelling out unnecessary tracking the 15 that were analysed were described in the codebook. Altogether 127 participants could be collected. Out of this number, only 112 cases will be analysed. This deficit occurs because some participants only answered some questions, and others were clearly not taking the survey seriously. The first was easily detected; the other could be partially identified by the time they used for the survey. This is the first collected variable. All participants using less than 5 minutes, an impossible duration for this survey, were excluded. This not guarantees that all respondents were fully committed to the survey but eliminates gross misconducts. Additionally, the response time for each answer was collected.

4. Analyses

The strategy of how the gathered data will be analysed is an important one. It limits the statements that can be made and is responsible for the possible conclusion that can be made out of them. Therefore a suitable choice has to be made, and its consequences have to be discussed.

The first section (4.1.) will describe some basic characteristics of the dataset and the respondents to see if the analysed sample represents the population. A second section (4.2.) will describe the found data, before the next section (4.3.) analyses the data with respect to the theoretical background. The last section (4.4.) looks at the data to see what limitations arise.

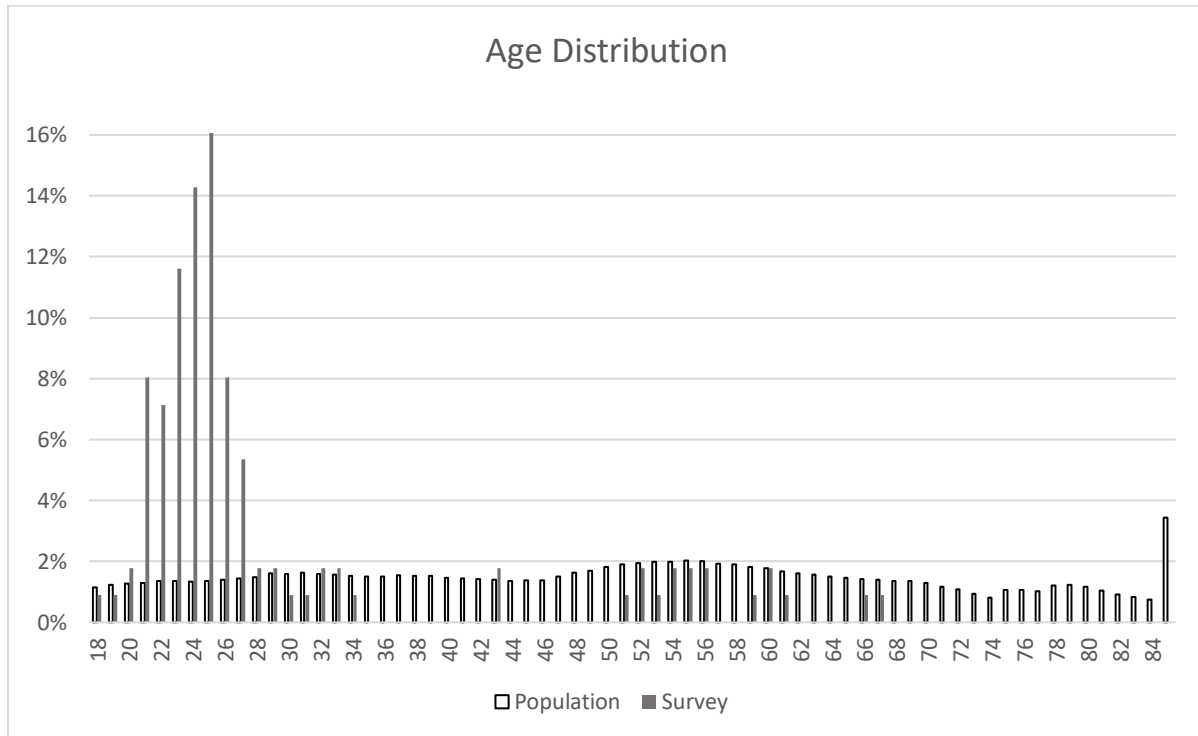
4.1. Descriptive of the Dataset and Respondents

In total 112 cases are analysed. To see if they are representative of the population, they will be compared to some general characteristics. First, the cases will be compared in the variables age, gender, and education with the population.

On the first question page of the survey, the participants were asked to answer the question: Which gender do you feel you belong to?. (“Welchem Geschlecht (Gender) fühlen Sie sich zugehörig?”(Survey: 2021)). 45,5% (51) of the resulting 112 cases stated that they were male, and 54,5 % (61) said they were female. No participant claimed to be non-binary. This can be compared with the population the cases were collected from. Therefore, the share of gender from all persons older than 18 years and currently live in Germany needs to be known. The data from September 2020 published by the Federal Statistical Office recorded 49.3% male and 50.7% female residents in Germany. (Statistisches Bundesamt: 2020). They, however, include minors and do not collect gender but sex. These data can still be used because they are approximately equal.

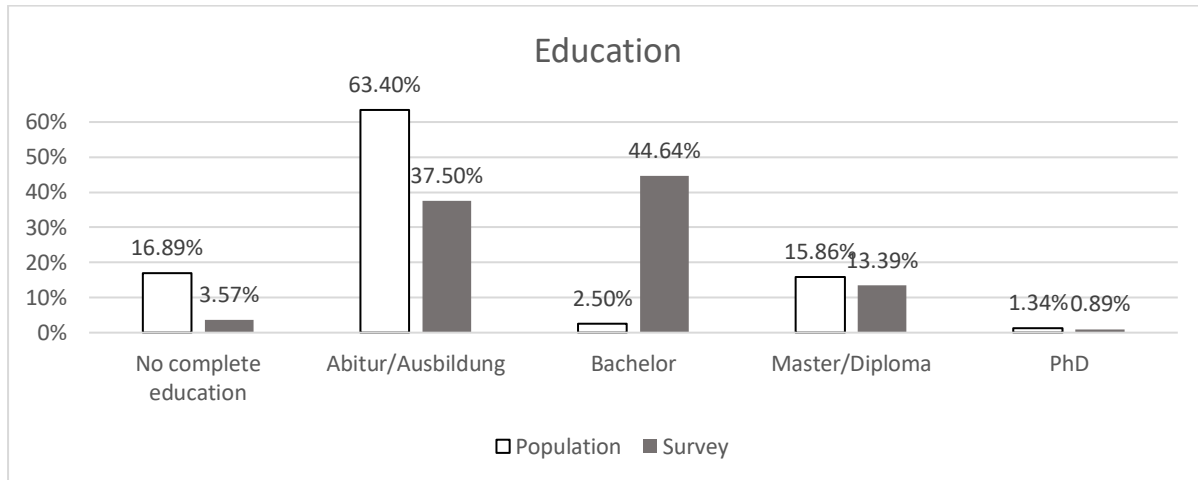
Next, the distribution of the age will be compared to the population. The 112 analysed cases were, on average (mean), 29,58 years old. The median was 25 years. Most participants (18) were 25 years old. 50% of the participants were between 23 and 28 years old, and 75% were younger than 28. The youngest participant was 18, the oldest 73. To calculate these numbers for the researched population is not possible. The officially collected either include the minors in the mean or if the data gets collected by birth year, all people older than 85 are one group. To compare the dataset with the population, the following Graphic has been created. Therefore information from the survey and the Federal Statistical Office has been used (Statistisches Bundesamt: 2021). A comparison can be seen in the Graphic below (Figure 7)

Figure 7: Age distribution of the sample



Another variable to compare the population with the used data set is education. Most of the participants (50) stated that they have a bachelor degree. This means nearly 45% of the selected cases. Four participants (4%) said that they did not get a high school diploma yet. Forty-two already had a high school diploma or finished an "Ausbildung", a professional training in Germany (38%). In the population (20 years or older), there are 17% without a high school diploma, 63% have one or an "Ausbildung". 3% got a Bachelor degree and 15% a Master degree or a university diploma. 13% of the participants had a master degree. Also, nearly 1% of the population and the sample had a PhD. (Statistisches Bundesamt: 2019). The following Visualisation (Figure 8) gives a good overview.

Figure 8: Distribution of Education in the sample and population



These numbers of the collected characteristics give a detailed picture of how representative the sample is concerning the population under study. The ratio of males and females is nearly the same in both sample and population. From population to sample, there is a difference of 3.8 percentage points in the share of men. Gender biased differences, therefore, do not need to be examined separately. The variable age, however, has fundamentally different expressions in sample and population. The distribution is extremely uneven. A significant share of the population is not represented in the sample. This affects primarily two groups, persons between 35 and 50 and persons over 60. This effect may derive from the fact that the survey was primarily spread online. This effect might also be an explanation for the differences in education between sample and population. The education level seems to be higher in the sample, and primary students were reached.

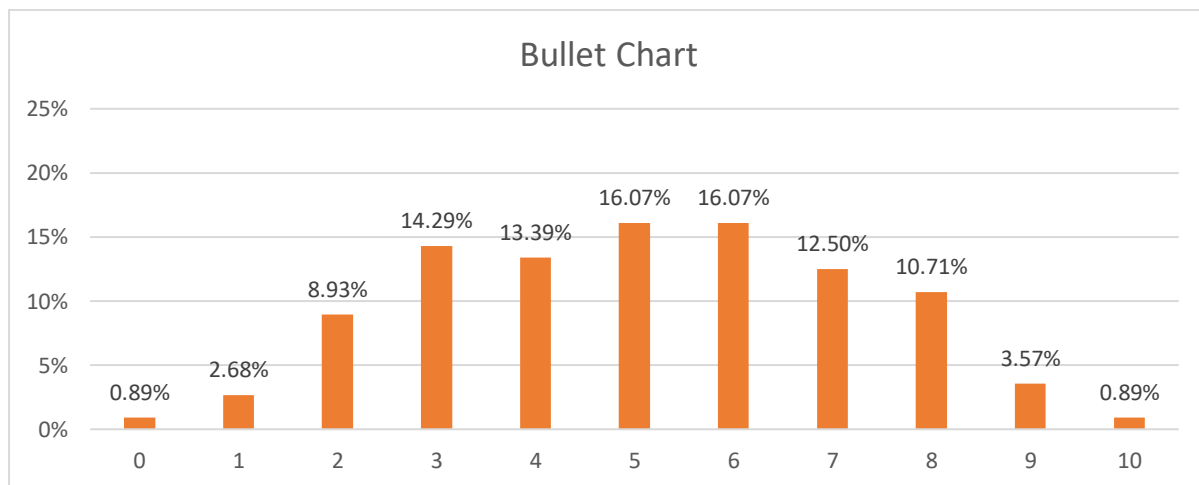
This makes clear that a unlimited transfer from the sample to the whole population is not possible. The subjects of this study are younger than the population and have a higher education (mainly students were reached). When trying to generalise the research, this sets the boundaries. This needs to be kept in mind when reading the following analyses and conclusion.

4.2. Data Description

This chapter will describe the findings of the collected data and explain how the unprocessed data was prepared to analyse them then. As already indicated, the dependent variable was collected after showing the participants the different graph types in randomised order. They reacted individually on each graph type once before they had to rank all graphs. The data that arise from these first six questions will now be described before the next chapter tries to interpret them.

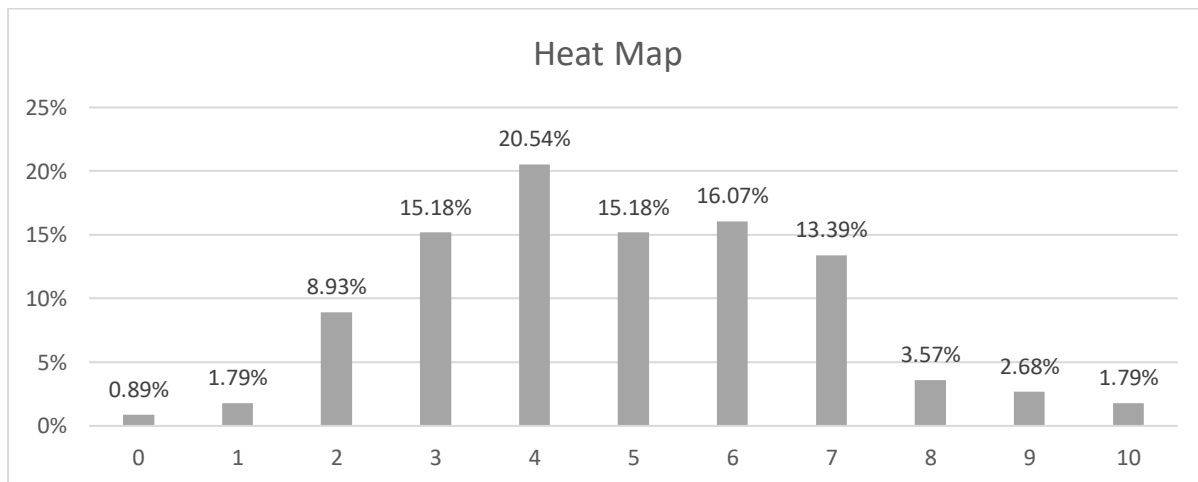
The first numbers that will be described represent the reaction to the Bullet Chart (Figure 9). Out of the 112 participants, 112 answered how high they think the riskiness was after looking at the presented visualisation. The average answer (mean) was 5.08, which has the meaning of the statement “somewhat risky” (5). The median for this graph type is 5. The middle 50% of the participants (25% to 75% Quartile) are between the numbers 3 and 7. The standard deviation is 2.148, and the variance 4.615. This distribution is almost symmetrical and has no relevant skewness (-0.017, non-standardised).

Figure 9: Perceived health risk- Bullet Chart



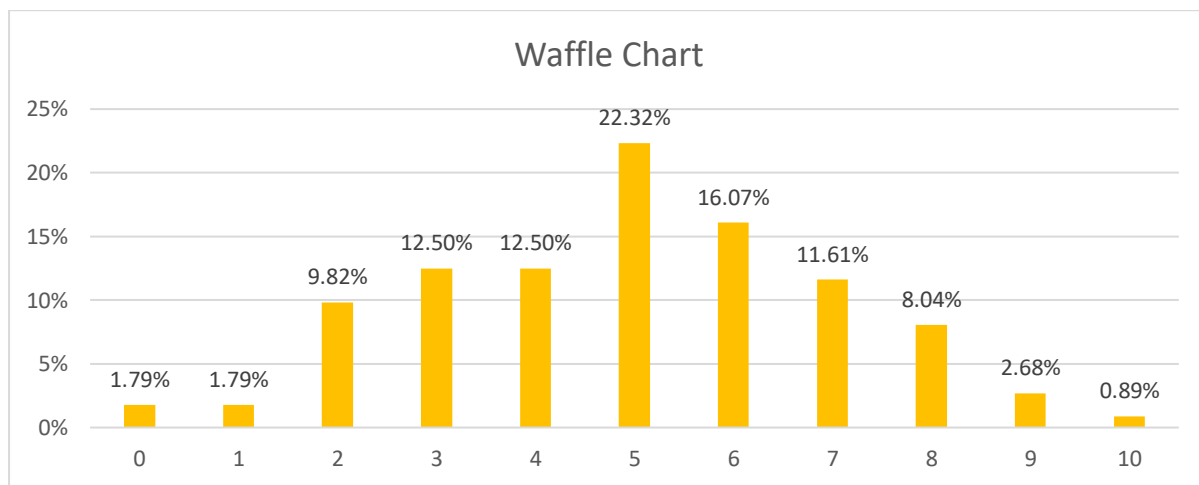
The second data that are now described represent the reaction to the Heat Map (Figure 10). Again 112 participants answered the question of how high they think the riskiness was after looking at the presented visualisation. The average answer (mean) was 4.84, which is near the statement “somewhat risky” (5). The median for this graph type is five, which means again “somewhat risky”. The middle 50% of the participants (25% to 75% Quartile) responded with numbers between 3 and 6. The standard deviation is 2.007 and the variance 4.028. This distribution has a very low positive skewness. It has a level of 0.252 (non-standardised) which means the frequent answers are slightly grouped at the left side of the scale).

Figure 10: Perceived health risk- Heat Map



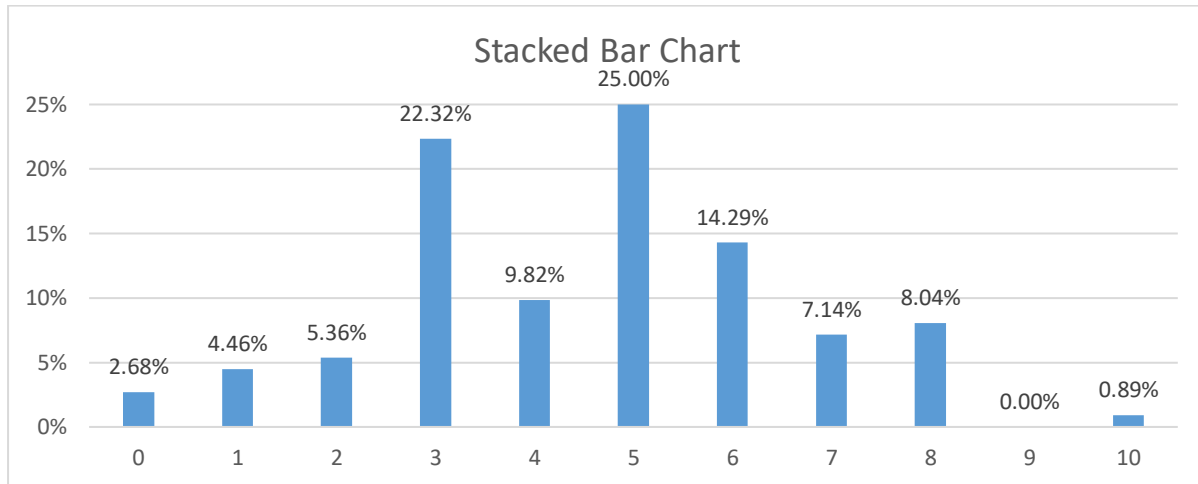
The following description of the figures represents the reaction to the Waffle Chart (Figure 11). All of the 112 participants answered the question of how high they think the riskiness was after looking at the Waffle Chart. The average answer (mean) was 4.96. The nearest statement connected to an interpretation was five and had the meaning of “somewhat risky” (5). The median for this graph type is also 5. The middle 50% of the participants (25% to 75% Quartile) are between the numbers 3 and 6. The standard deviation is 2.068, and the variance 4.277. There is almost no skewness (-0.057, non-standardised).

Figure 11: Perceived health risk- Waffle Chart



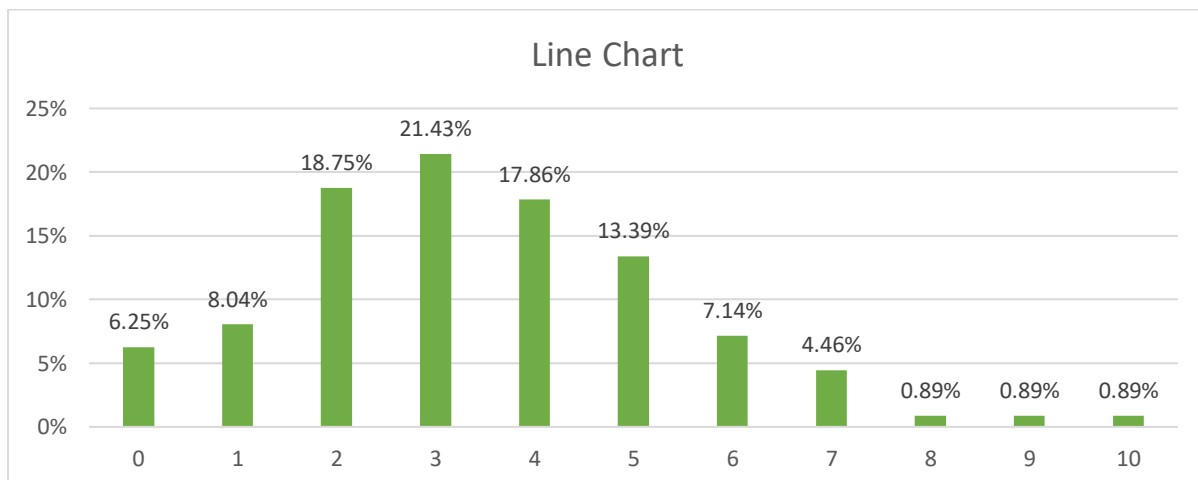
The fourth data that will be described represent the reaction to the Stacked Bar Chart (Figure 12). All 112 participants answered the question on how high they think the riskiness was after looking at the Stacked Bar Chart. The mean of all answers was 4.55, again also is interpretable, with the statement “somewhat risky” (5). The median for this graph type is 5. The middle 50% of the participants (25% to 75% Quartile) are between the numbers 3 and 6. The standard deviation is 2.017 and the variance 4.069. The skewness of this data also has no clear positive or negative trend (-0.006, non-standardised).

Figure 12: Perceived health risk- Stacked Bar Chart



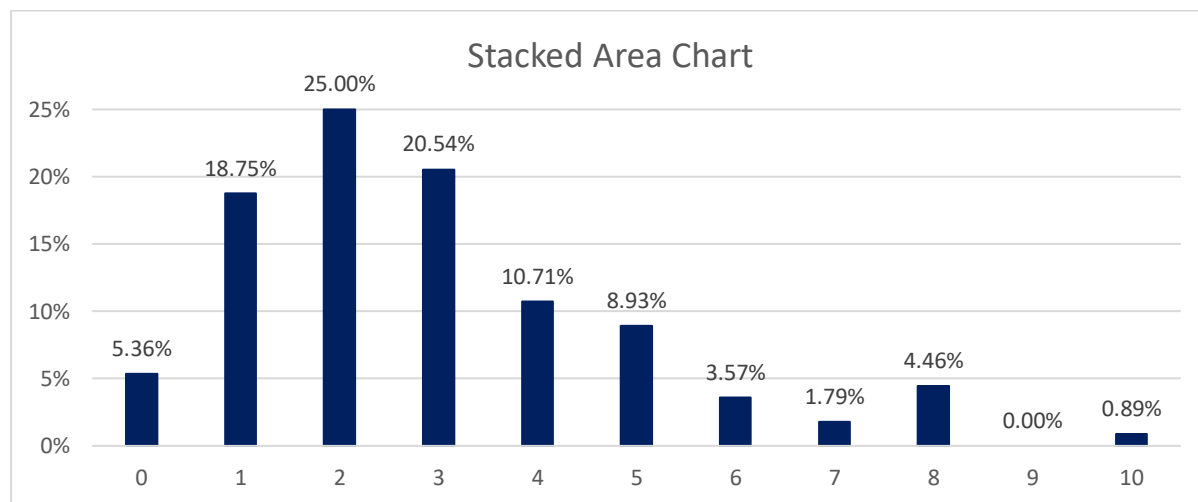
The fifth set of answers belongs to the Line Chart and derived from the answers to how high the riskiness was after looking at the presented visualisation. (Figure 13) All 112 participants answered. Together they had a mean of 3.46, which has a meaning that is between the statements “as risky as usual” (0) and “somewhat risky” (5). The median for this graph type is 3. The middle 50% of the participants (25% to 75% Quartile) are between the numbers 2 and 5. The standard deviation is 1.986, and the variance is 3.945. However, the skewness of the distribution indicates a medium positive skew (0.535, non-standardised), which means that more answers are on the lower side of the scale.

Figure 13: Perceived health risk- Line Chart



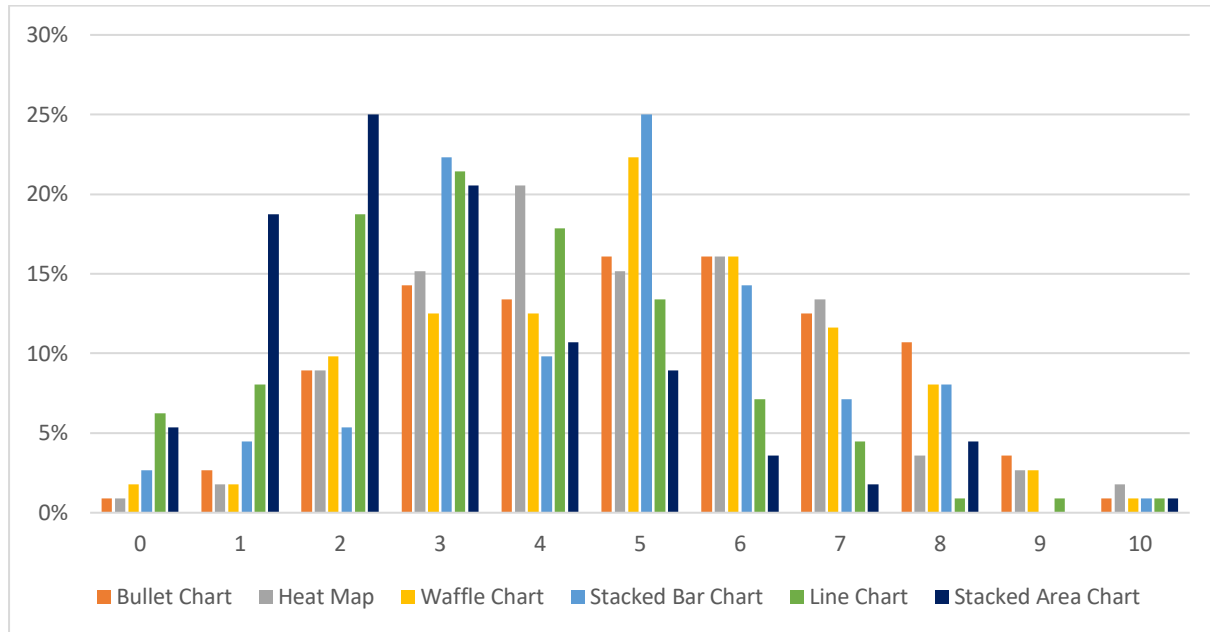
The last numbers that will be described represent the reaction to the Stacked Area Chart. All of the 112 participants answered the question of how high they think the riskiness was after looking at the Stacked Area Chart. The average answer (mean) was 2.96, which means something between the statements “as risky as usual” (0) and “somewhat risky” (5). The median for this graph type is 3. The middle 50% of the participants (25% to 75% Quartile) are between the numbers 2 and 4. The standard deviation is 2.035, and the variance 4.143. The skewness of this distribution reaches a level of 1.074 (non-standardised) which indicates that the data are clustered by the lower end of the scale.

Figure 14: Perceived health risk- Stacked Area Chart



All visualisations together in one graph can be seen in Figure 15. It shows all perceived health risks together and gives an impression of the overall risk perception. It suggests that the most risk perceptions of the individual graphs are in the same range. It becomes clear that the Line Chart and the Stacked Area Chart are the ones that imply the lowest health risk to the participants. Also the normal distribution of the perceived health risks by the other visualisations becomes more apparent.

Figure 15: Perceived health risks



4.3. Analyses amid the theoretical background

The data will be analysed with the help of a statistical evaluation. Since the personal health risk dependence on the visualisation form is to investigate, a few limitations to the statistical process occur. The different visualisation forms cannot be ranked among themselves; they have a nominal scale level. This limits the available statistical correlation measures. The level of personal health evaluation is at least ordinal. This means that coefficients for two nominal variables will be analysed. That is because the lowest scale level must be considered when choosing the statistical tests. The choice for them is, on the one hand, Cramér’s V, on the other, an analysis of variance (one-way ANOVA). These are two often used methods. They have a relatively simple application and are therefore an excellent usable option. On this basis, conclusions will be drawn.

The analysis of variance will be the first thing this research deals with. Using analysis of variance makes it possible to calculate if the means of several experimental conditions differ significantly from each other. A univariate ANOVA compares the values of a quantitative dependent variable across multiple groups of a categorical independent variable. Therefore the ANOVA used here is an analysis of the (variance) differences between all 6 visualisation forms. The ANOVA gives out two values to

interpret. The first one is the F-value. If the variance within categories is lower than the variance between categories, the F-test produces a higher F-value and thus a higher probability that the observed difference is genuine and not due to chance. The F-value can be compared to the critical F-value that should be lower for statistical relevance. The second value is the significance. This value should be as low as possible. From a value below 0.05, the Null-hypotheses must be rejected, and therefore a significant difference between the different means is present.

The ANOVA in this research reports statistical significance ($f=20.771$, $p<0.001$) with a critical F-value of 2.23 ($\alpha=0.05$, $df_1=5$, $df_2=666$) (Table 1).

The next performed test is Cramér's V. Cramer's V is the standardised value of the correlation measurement chi-squared. The already described p-value, which was close to zero, indicates that the variables are unlikely to be completely unassociated. However, this does not mean the variables are strongly associated. Cramér's V can indicate how strongly two categorical variables are associated. A value between zero and one represents the connection. One represents a complete relation, while zero indicates full independence. The values of this test produced by this research indicate a weak connection (0.209, $p<0.001$). So there is an association of the two analysed variables.

Now the in chapter 4.2. described findings, the characteristics of the dependent variable will be described in each category of the independent variable. The perceived health risks of the participants will be analysed amid the findings of the theoretical background. Therefore the three sub-questions and the and the associated predictions will be the reference. Based on this the two hypothesis shall be reviewed.

Sub-questions

The first sub-question was "Does using Bullet Charts versus Heat Maps in Corona-data-visualisations affect people's assessment of their health risks?". It was expected that Heat Maps lead people to assess their health risk slightly higher than Bullet Charts. A quick mean comparison shows that they both reach very similar values. The Heat Map has a mean of 4.84 and a median of 5. The Bullet Chart a mean 5.05 and a median of

5. A two tailed paired t-test shows no significant differences between the means. ($p > 0.05$) (Table 3) The expected low difference cannot be confirmed, in this research.

The second sub-question was “Does the usage of Waffle Charts versus Stacked Bar Charts in Corona-data-visualisations affect people's assessment of their health risks?”. The theory suggested that Waffle Charts lead people to assess their health risk the same high as Stacked Bar Charts. Comparing the mean and mediana gives a first insight to what extent this is as expected. The mean of the data connected to the Waffle Chart has a value of 4.96, the Stacked Bar Chart reaches a level of 4.55. The Median for both visualisation forms is 5. Both forms share only slightly different values. A two tailed paired t-test that compares the means shows significance ($p = 0.008$) (Table 3). The expected missing difference can be confirmed by this data, to the extent that there is only a little difference.

The third sub-question was “Does the usage of Line Charts versus Stacked Area Charts in Corona-data-visualisations affect people's assessment of their health risks?”. The expectation was that Stacked Area Charts lead people to assess their health risk slightly lower than Line Charts. A comparison of mean and median show the following. The Stacked Area Chart has a mean of 2.96 and a median of 3. The Line Chart has a median of 3.46 and also a median of 3. The two tailed paired t-test for this mean comparison also shows significance ($p = 0.002$) (Table 3). The prediction that the Stacked Area Chart has slightly lower values can therefore be confirmed.

As a result it is arguable that the predictions to the three sub-questions were correct to a certain extent. This supports the statement that the formulated hypotheses were able to explain a part of the observed findings.

Comparison of the Families

Now a deeper look into the observations is possible, it will help to explore the causes of the result. This happens within the different visualisation families.

The group of the Categorical Charts contains the visualisation types Heat Map and Bullet Chart.

The first analysed graph is the Bullet Chart. The Bullet Chart attracts attention because its values have nearly a normal distribution. It was expected that because of the extensive use of colour with equal colour shares, which according to the theory section should have no effect on the perceived health risk, and the continuous time axis, which should decrease the perceived health risk, the Bullet Chart does evoke health risks a bit below the average. This assessment seems to have been accurate.

In contrast to that, the Heat Map should have raised a higher perceived health risk. This was expected because the amount of used colour as a reference point was high and contained more green and the time axis was not one single axis. However, the achieved values are similar (even a bit lower) in contrast to those of the Bullet Chart. This might come thru the fact that the representation of the course of time of the Heat Map was not understood as continuous because it was split up into two axes. The recipients, however, might have seen it as continuous or at least very detailed and therefore implied a lower health risk as the theory expected.

The fact that the Bullet Chart is far more detailed and allows the recipient to make a more detailed distinction in the risk assessment of a particular day, seems to have no relevant influence or an influence that does not collide with the predictions that arise from the theory. The situation is similar concerning the fact that the Bullet Chart is a graph that is often used during the Corona-pandemic (Kwon et al., 2021). The specific underlying data in these visualisations have set the tone the perceived health risk varies in, which is nearly the same for all visualisations, the differences in colour and time axis only have slight impact.

The Waffle Chart and the Stacked Bar Chart are visualisation forms of the Hierarchical Charts family.

The Waffle Chart will be the third graph in this chapter that will be analysed and compared. The values described in the previous chapter (4.2.) do not show

striking deflections in either direction. The same can be said for the Stacked Bar Chart. They both do not include a continuous time axis and use a lot of colour. Therefore, it was anticipated that both of these visualisations arouse the same high health risk. This in combination with the used data, which for many participants' represent a not too threatening Corona-situation in general, means a medium to low level. The data of the survey confirm this.

The last chart family that will be analysed is the family of the Temporal Charts. This family includes the Stacked Area Chart and the Line Chart.

The theory in combination with the presented data suggested that the Stacked Area Chart should cause a very low health risk perception because it combines a continuous time axis and heavily uses colour. On the other hand, the Line Chart should cause a low health risk perception because the continuous time axis and the little use of colour should decrease the health risk perception. Both charts behaves as expected. As the previous chapter describes, a low health risk perception was reported after viewing this graph.

Research question

Now it is possible to tackle the research question. To see if the usage of different chart families affect people's assessment of their health risks, the three chart families among themselves will now be compared. The expectations derived from the theory were that the hierarchical charts lead people to assess their health risk the highest and that the temporal charts lead to the lowest health risk assessment. The categorical charts come in between. The findings from the survey, however, suggest a slightly different order. The categorical and hierarchical families both cause the same medium to low health risk perception. The temporal charts indeed imply a lower health risk than the other categories. Besides the already made arguments about the share of colour used in the visualisation and the dependence on a continuous time axis, the purpose of the different families will now be taken into account.

The family of categorical charts and especially the graphs chosen from here are specialised in comparing data. So the comparison of different time periods within

the entire period under investigation seem whether to increase nor decrease the health risk perceived.

The hierarchical charts, in particular, the selected two, are designed for "revealing part-to-whole relationships and hierarchies" (Kirk, 2019). So in principle, it comes back to comparing different time periods within on graph that visualises the whole period under research. This is helpful when explaining why the visualisation from both this family is so similar.

On the other hand, the two used temporal charts are designed for "plotting trends [...] over time" (Kirk, 2019). This focus on visualising a detailed development over time might strengthen the effect that graph forms with a continuous time axis lead the recipients to transfer the implied health risks of the data visualisation to the whole shown time range. (Ancker et al., 2006) This effect is independent from the underlying data set. Increasing as well as decreasing trends, high data as well as low data, both are influenced by the effect of the continuous time axis. The continuous time axis decreases the implied health risk independent of the intrinsic data value. The health risk perception gets relatively lowered when the continuous time axis is part of the visualisation Another aspect that should be taken into account here is the cumulative character that these two visualisations have. Showing the data cumulative might have an effect on the perceived health risk and should be researched further.

4.4. Limitation

This chapter focuses on restrictions that the findings of this research bring along, besides the already discussed limited generalization due to the unrepresentative sample. There are still several directions the restrictions could accrue from. Statistical methods, as well as incoherent findings and problems in the basic structure, will be discussed.

The in the analyses used ANOVA is based on three assumptions. The independence of observation, normal distributed response variables and homogeneity of variance. In general, they can be taken as given according to the information already presented. However, the independence of observation may suffer from interfering third variables,

which is a general weakness within this research. Although the plan for the theoretical structure should eliminate interfering variables, this cannot be guaranteed. The effects that a visualisation has on the recipients are extremely broad, and closer observation of more aspect should be the content of further research.

Another aspect that limits the presented findings occurs through the variable that was measured to check the findings. To analyse the differences between two or more of the presented visualisations is not possible because the answers to this question only indicate an order and not comparable values. The participants ranked the visualisation in the survey by the perceived riskiness. The ANOVA for this reports statistical significance ($f=21.099$, $p<0.001$) with a critical F-value of 2.23 ($\alpha=0.05$, $df_1=5$, $df_2=591$) (Table 2). Cramér's V, on the other hand, indicates that these variables (visualisation type and rank) are associated. The values of this test indicate an existing medium connection (0.376, $p<0.001$).

However, the first qualitative analyses of this data do not suggest complete similar findings compared to the previously analysed data. On the one hand, the data from these here presented direct comparisons, the rankings (Figure 16 &17) are systematically different from the qualitative evaluations that the standalone question delivered. On the other hand, these findings lead to treating the findings of the previous analyses more carefully.

Figure 16: The share of ranks of the individual visualisations got.

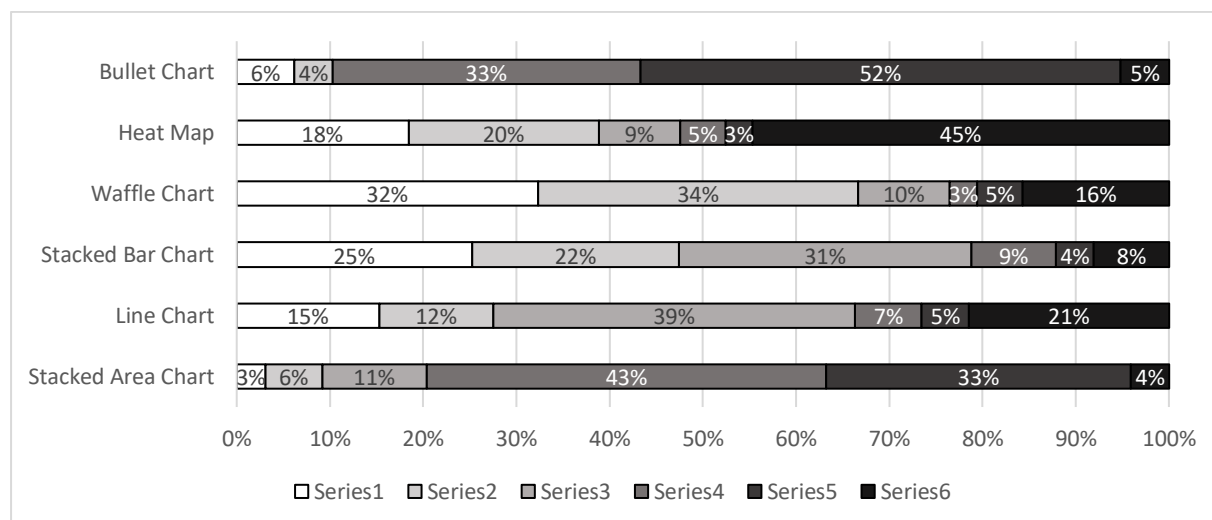
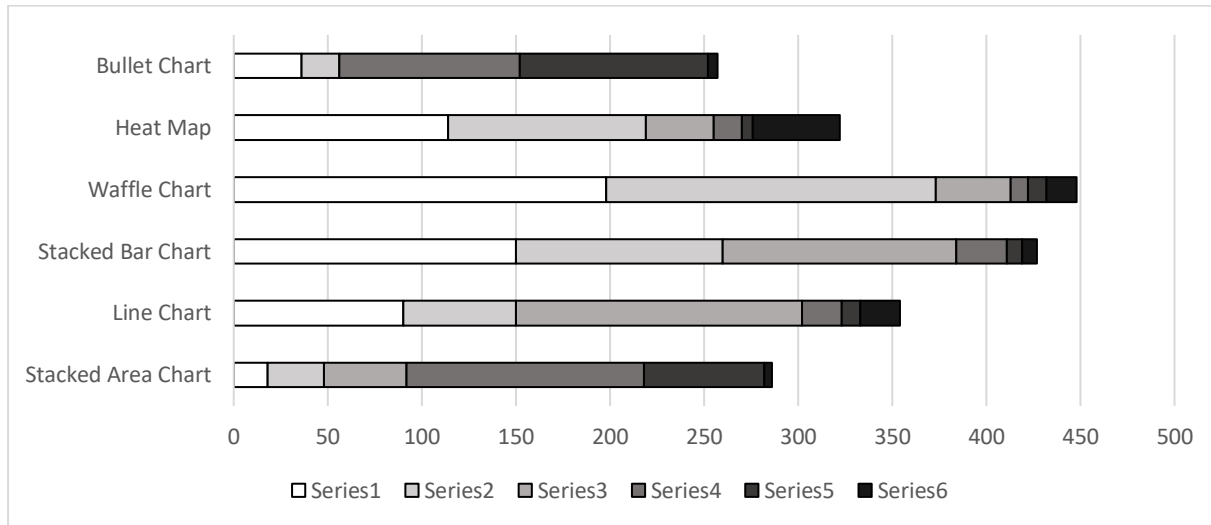


Figure 17: The frequencies of the ranks multiplied with the rank values.

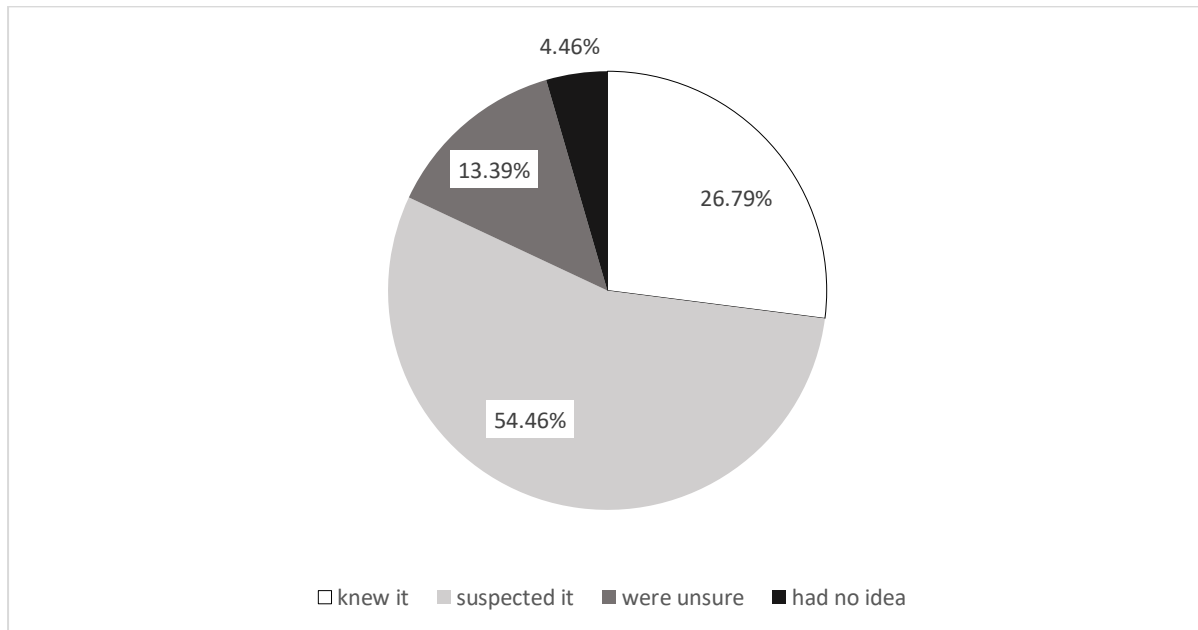


This first figure shows the share of ranks that each visualisation got. The second figure visualises the order that the ranking question suggests. Therefore the ranks were weighted and multiplied with the number of times the visualization got voted on the specific rank. The Waffle Chart is the in total highest ranked visualisation which means that it indicated the highest health risk in relation to the other visualisations, but says nothing about how high the indicated health risk was. The Bullet Chart was the one that indicated the lowest health risk. The order that Figure 17 suggests is different from the order that the stand alone question intended. This effect could be analysed in further research but for now has to be seen as a limitation to the findings.

The question of how many participants could answer the questions of this survey unbiased is also interesting. If participants knew what the intent of the survey was, the answers might be biased. So the last question of the survey tried to figure out if the participants knew if all visualisations include the exact same data. The findings were visualised in Figure 18. About a quarter said that they knew that all graphs visualised the same data. Near the half claimed that they suspected this. To conclude, this also must be seen as a limitation because not all participants were unbiased, because they already suspected what the different treatments were. This could mean that they suspected what this research was about and therefore gave answers that they thought would be correct, and not indicated their real perception. A analyses without the group that acted this way would have be beneficial for the research. However this would have

limited the number of cases that could be statistical analysed, to a level where statistical analyses gets difficult because of the then occurring lack of informative and significant value.

Figure 18: How many participants knew that all graphs visualised the exact same data.



5. Conclusion

The last chapter of this research will shortly conclude the findings of this research before they are discussed. After that the scientific relevance and a view on further research will be provided.

This research is built around three sub-questions, they aim at differences in the perceived health risks within three families of charts. These three questions together anticipated how the three chart families (hierarchical, categorical, temporal) would influence the perceived health risk of the presented COVID19-Visualisations. The influences of the aspects share of colour and usage of continuous time axis were examined besides the design intentions of the families.

The three sub-questions which researched the differences of two visualisations in each family, found that within the families the visualisations produce no great differences in the perceived health risks. The families among each other however show some differences. The temporal chart family (with its cumulative visualisations) caused a decrease in the perceived health risk, especially in contrast to the other two families that

both reached a medium level. This verifies the two hypotheses, that a higher share of green and a continuous time axis lowers the perceived health risk perception, to a certain extent. To conclude the research question, if the usage of different chart families affects people's health risk assessment can be answered affirmatively.

The research however suffers from a unrepresentative sample that includes more young and well educated people, an insufficient exclusion of interfering variables due to its theoretical setup, a high proportion of study participants who gave biased answers and a self-reported control variable that could not reproduce the results.

Nevertheless this research could show that the interaction between form and content of visualisation is far more relevant than thought. The underlying data set has a significant influence on what the visualisations imply. This can be linked to the theory. It is important to notice, that this implies a future episode in this research field that detailed focusses on this aspects is necessary. The detailed research on how individual aspects of visualisation influence people forms should be extended to include aspects that take into account the interaction between form and content. This is highly relevant for the relevant practice of creation and targeted distribution of visualisations.

The researched visualisation forms however are able to slightly decrease this basic level of the health risk assessment. This and the already described findings are a part of the originating scientific relevance. Further research however could extend this findings and verify the first impressions that emerged here. This research could focus on the influence of cumulative visualizations and to what extend this characteristic influences the here presented findings. However, this research shows that for application in practice temporal charts with cumulative character lowers the perceive health risk in contrast to hierarchical and categorical visualisations.

List of references

- Ancker, J. S., Senathirajah, Y., Kukafka, R., & Starren, J. B. (2006). Design Features of Graphs in Health Risk Communication: A Systematic Review. *Journal of the American Medical Informatics Association*, 13(6), 608–618. <https://doi.org/10.1197/jamia.m2115>
- Christmann, C. A., Zolynski, G., Hoffmann, A., & Bleser, G. (2017). Effective Visualisation of Long Term Health Data to Support Behavior Change. *Digital Human Modeling. Applications in Health, Safety, Ergonomics, and Risk Management: Health and Safety*, 237–247. https://doi.org/10.1007/978-3-319-58466-9_22
- Engebretsen, M., & Kennedy, H. (2020). *Data Visualization in Society*. Amsterdam University Press. <https://doi.org/10.5117/9789463722902>
- Flick, U. (2009). *Sozialforschung: Methoden und Anwendungen: Ein Überblick für die BA-Studiengänge* (5. ed.). Rowohlt Taschenbuch.
- Ganzach, Y., Ellis, S., Pazy, A., & Ricci-Siag, T. (2008). On the perception and operationalisation of risk perception. *Judgment and Decision Making*, 3(4), 317–324. https://www.tau.ac.il/~yoavgn/files/perception&operationalization_risk.pdf
- Herring, J., VanDyke, M. S., Cummins, R. G., & Melton, F. (2016). Communicating Local Climate Risks Online Through an Interactive Data Visualization. *Environmental Communication*, 11(1), 90–105. <https://doi.org/10.1080/17524032.2016.1176946>
- Kennedy, H., & Hill, R. L. (2018). The Feeling of Numbers: Emotions in Everyday Engagements with Data and Their Visualisation. *Sociology*, 52(4), 830–848. <https://doi.org/10.1177/0038038516674675>
- Kennedy, H., Weber, W., & Engebretsen, M. (2020). Data visualisation and transparency in the news. In *Data Visualization in Society* (pp. 169–185). Amsterdam University Press. https://doi.org/10.5117/9789463722902_ch11
- Kirk, A. (2019). *Data Visualisation* (2nd ed.). SAGE Publications.
- Kwon, O. N., Han, C., Lee, C., Lee, K., Kim, K., Jo, G., & Yoon, G. (2021). Graphs in the COVID-19 news: a mathematics audit of newspapers in Korea. *Educational Studies in Mathematics*. Published. <https://doi.org/10.1007/s10649-021-10029-0>
- Landeszentrum Gesundheit Nordrhein Westfalen. (2021). *Corona-Meldelage - LZG.NRW*. Corona-Meldelage - LZG.NRW. https://www.lzg.nrw.de/inf_schutz/corona_meldelage/index.html
- Lee, C., Yang, T., Inchoco, G. D., Jones, G. M., & Satyanarayan, A. (2021). Viral Visualisations: How Coronavirus Skeptics Use Orthodox Data Practices to Promote Unorthodox Science Online. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Published. <https://doi.org/10.1145/3411764.3445211>
- Li, Q. (2020). *Embodying Data*. Springer. <https://doi.org/10.1007/978-981-15-5069-0>

Lipkus, I. M., & Hollands, J. G. (1999). The Visual Communication of Risk. *Journal of the National Cancer Institute Monographs*, 25, 149–163.
<https://academic.oup.com/jncimono/article/1999/25/149/897831>

Masson, E., & van Es, K. (2017). *The power of evidentiary regimes in speculative data visualisation* [Slides]. <https://doi.org/10.22215/Datapower.V2017i0.60>.
<https://conference.library.carleton.ca/index.php/datapower/article/view/60>

Nærland, T. U. (2020). The political significance of data visualisation: Four key perspectives. In *Data Visualization in Society*. (pp. 63–73). Amsterdam University Press.

Sevi, S., Aviña, M. M., Péloquin-Skulski, G., Heisbourg, E., Vegas, P., Coulombe, M., Arel-Bundock, V., Loewen, P. J., & Blais, A. (2020). Logarithmic versus Linear Visualizations of COVID-19 Cases Do Not Affect Citizens' Support for Confinement. *Canadian Journal of Political Science*, 53(2), 385–390. <https://doi.org/10.1017/s000842392000030x>

Sheppard, S. R. J. (2005). Landscape visualisation and climate change: the potential for influencing perceptions and behaviour. *Environmental Science & Policy*, 8(6), 637–654.
<https://doi.org/10.1016/j.envsci.2005.08.002>

Sniderman, P. M. (2011). The Logic and Design of the Survey Experiment. In J. N. Duckman, D. P. Green, J. H. Kuklinski, & A. Lupia (Eds.), *Cambridge Handbook of Experimental Political Science* (pp. 102–114). Cambridge University Press.

Statistisches Bundesamt. (2019). *Bildungsstand der Bevölkerung*. Statistisches Bundesamt.
https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Bildungsstand/Publikationen/Downloads-Bildungsstand/bildungsstand-bevoelkerung-5210002197004.pdf?__blob=publicationFile

Statistisches Bundesamt. (2020). *Bevölkerungsstand - Bevölkerung nach Nationalität und Geschlecht (Quartalszahlen)*. Statistisches Bundesamt.
<https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-zensus-geschlecht-staatsangehoerigkeit.html>

Statistisches Bundesamt. (2021, June 28). *Statistisches Bundesamt Deutschland - GENESIS-Online: Die Datenbank des Statistischen Bundesamtes*. Statistisches Bundesamt.
<https://www-genesis.destatis.de/genesis/online?operation=abruftabelleBearbeiten&levelindex=1&levelid=1623419428873&auswahloperation=abruftabelleAuspraegungAuswaehlen&auswahlverzeichnis=ordnungsstruktur&auswahlziel=werteabruf&code=12411-0005&auswahltext=&werteabruf=starten#abreadcrumb>

Trajkova, M., Alhakamy, A., Cafaro, F., Vedak, S., Mallappa, R., & Kankara, S. R. (2020). Exploring Casual COVID-19 Data Visualisations on Twitter: Topics and Challenges. *Informatics*, 7(3), 35–57. <https://doi.org/10.3390/informatics7030035>

Appendix

Table 1

ANOVA	Sum of Square	df	Mean Squares	F	Sig.
Between the Groups	434.065	5	86.813	20.771	0.000
Within the Groups	2783.554	666	4.180		
Total	3217.619	671			

Critical F value (alpha 5%): 2.2276

Table 2

ANOVA	Sum of Square	df	Mean Squares	F	Sig.
Between the Groups	265.555	5	53.111	21.099	0.000
Within the Groups	1487.661	591	2.517		
Total	1753.216	596			

Critical F value (alpha 5%): 2.2293

Table 3

95% Confidence
interval of the
difference

two tailed paired t- test	Mean difference	Std. deviation	Std. Error Mean	lower value	higher value	T	df	Sig. (2- tailed)
Bullet Chart/ Heat Map	0.241	2.068	0.195	-0.146	0.628	1.234	111	0.220
Waffle Chart/ Stacked Bar Chart	0.402	1.574	0.149	0.107	0.696	2.702	111	0.008
Line Chart/ Stacked Area Chart	0.500	1.677	0.158	0.186	0.814	3.156	111	0.002

Data Appendix

Codebook, Figures and Visualisations

SPSS Data Set 1

SPSS Data Set 2

SPSS Data Set 3

SPSS Output 1

SPSS Output 2

SPSS Output 3

SPSS Syntax 1

SPSS Syntax 2

SPSS Syntax 3

Survey 2021