The effects of visual representation and personal relevance on understanding and perception of visual data

Lucie Göbbels

S1016341

Abstract

This paper summarizes and analyses the results of an experimental study concerning the effects of personal relevancy and visual representation of Covid-19 data on understanding and perception of the graphics used.

The study found no significant effects of either independent variable on either dependent variable, but nevertheless urges for more research to be done in this field, as the literature it is based on strongly suggests that relevancy and visual representation could have an impact on understanding and perception of graphical data in a real-world setting.

Introduction

Designing visual representations of data is a task of high social relevance: whether data is meant to help a viewer decide which medication to take, what purchasing choice to make or visualize which political parties are popular at the moment, it is imperative that the viewer is able to understand and interpret the data correctly or according to the graph designer’s wishes.

There are several layers to graph understanding and, subsequently, interpretation: the process of graph understanding itself, the framing and presentation of the graph, including factors such as prior knowledge of the viewer and the visual choices such as graph type, and, finally, the interpretation of the graph, which is again dependent on prior knowledge, potential prejudices and personal factors such as risk taking.

Most research nowadays agrees that there are three fundamental stages to graph understanding: elementary comprehension, intermediate understanding (such as recognizing trends) and extrapolation of information and interpretation of the implications of the data (Friel, Curcio & Bright, 2001).

These levels of graph understanding have been investigated thoroughly, with several factors being identified as important variables that can affect the readers’ abilities to correctly read and interpret visual information (Friel et al, 2001): Graph complexity, reader characteristics (e.g., logical thinking and experience with reading graphs), the type of task that is assigned (e.g., is the reader only instructed to read certain values from the graph, or are they being asked about the implications and consequences of the data they are presented with?) and graph contextualization (meaning, is the graph labelled and provided with a real-world context?).

However, all of these factors are reliant on a situation in which the reader actually pays close attention to the graphs. Most studies that investigate graph understanding and interpretation give the reader no choice but to engage with the visual information, however, this is not how graph perception usually works in the real world: when seeing graphs in a newspaper or on a website, the reader has a) a choice whether they want to engage with the information at all and b) a choice to what extent and for how long they want to engage with the information.

Therefore, bringing attention to a graph in the first place is also a relevant task for designers and researchers alike.

Evergreen & Metzner (2013) name several characteristics that graphic designers usually employ to facilitate attention to graphics and data visualization, namely simplification, legend, colour, and a reduction of data that is present in the graphic. While these are generally applicable to graphic design and in most cases do make it easier to read and understand a graphic, they do not guarantee that the message will actually be processed in an attentive way that makes the onlooker understand the visualization. However, it is helpful to emphasize that attention and visual appeal are closely linked.

From the literature so far discussed, it can be stated that the ideal graph would be easy to understand, command the attention of readers, and would be visually appealing and/or engaging enough to maintain that attention.

A factor that may aid both with directing and maintaining the reader's attention to graphics as well as with understanding the information is relevance. The personal connection that a viewer has to the data, the perceived social relevance of the data and the relative importance of the data compared to other things available in their vision have been linked to graph attention and may also contribute to better graph understanding.

Namely, Bucher & Schumacher (2006) state that "media reception is an active process of selection", and competence, experience as well as objectives and values are assumed to influence the types of media that a person consumes (keeping in mind this study focused on news articles, not graphics).

There is relatively little research about relevance affecting perception and understanding of graphics, and the gap in the research that has been done is clear: most of what is available focuses on the relationship between relevance and graph liking (see Peck, Ayuso & El-Etr, 2019) or on the relevance and subsequent interpretation in textual messages. With very little to base oneself on, it is difficult to form a coherent picture of what this presumed connection between relevance and understanding of visual information might look like, but from research about related concepts and similar theories, some important tendencies can be discovered.

Firstly, the Elaboration Likelihood Model (ELM) proposed by Petty & Cacioppo (1986) states that with higher motivation, ability, and opportunity to process, a message will be processed more elaborately via the central route, meaning that the message will not only be processed peripherally and via superficial clues, but the viewer will actively engage with the message cognitively and employ previous knowledge to interpret it (for a detailed model, see the appendix). Though this model does not focus on visual representations, it has been widely employed in advertising research (Sher & Lee, 2009, as well as Teeny, Briñol & Petty, 2017), so it can be assumed that its effects do not only pertain to textual information.

Keeping this in mind, it would be ideal for data visualization to be faced with a viewer that is highly motivated, has high ability and high opportunity to process. One can assume that ability and opportunity are difficult to control. In the case of data visualization, they would relate to factors such as being able to read graphs, numeracy, time available and ability to understand background information. On the other hand, motivation relies on attitudes towards the message, as the ELM claims that if a message goes against a person's previously established beliefs, they are less motivated to process it centrally, need for cognition (individuals with a higher need for cognition tend to process messages more centrally) and, crucially, personal relevance.

Therefore, we can conclude from the ELM that personal relevance may lead to more central processing, meaning the viewer will likely pay more attention to details and focus on the actual information presented rather than peripheral cues such as colours, structure of the graph and surrounding elements.

The effects of personal relevance in data perception have been investigated in connection with graph liking and graph preference – for instance, Peck et al (2019) asked residents of rural areas in Pennsylvania to pick graphics that they were interested in and that appealed to them from a selection of various graphics and visuals. When asked for the reasoning behind their choices, many of them cited personal relevance. For example, a graphic about drug use was often chosen over other graphics when that person or someone close to them had a history with addiction.

However, not only personal relevance was found to be a factor in their selection, but social relevance as well – the participants were aware of the larger struggles their community was facing and selected graphs that would be helpful to others and easily understood by people they knew.

Similarly, Okan, Stone & Bruine de Bruin (2018) chose to ask participants about their perceived understanding of the graphs they saw (which were related to visual health communication) and how well they liked the graphs they were shown. Liking and relevancy appear to be interrelated, as Peck et al (2019) also cited subjective liking as a reason why people chose to view or interact with certain graphs.

Nevertheless, as a whole, the concept of relevance has only been investigated sporadically and in very specific circumstances and, as in the case of Peck et al (2019), with very limited groups of participants.

Connected to the concept of personal relevance, previous knowledge and experience with the topic is also a relevant factor that has been identified by the research to aid graph understanding and interpretation.

For example, (Glazer 2011) points out several theories and models in a literature review on graph comprehension that include factors such as prior knowledge, familiarity with the topic or previously established beliefs. A study by Shah & Hoeffner (2002) even demonstrated that established beliefs about the world (in this example, the belief that an increase in drunk driving leads to an increase in car accidents) can lead to misinterpretation of the graphical information. In this case their study demonstrated how seeing a relationship between drunk drivers and car accidents was possible for participants even if this was not explicitly represented within the visual information.

As it stands, graph understanding, liking, interpretation and even the amount of attention that readers give to graphical information in the first place is potentially deeply affected by how personally or socially relevant they perceive the information to be, how much prior knowledge they have about the topic and also about graphs in general and their beliefs and biases about the topic at hand.

Additionally, the type of graph that viewers need to interpret can lead to differences in their perception of the information that the graph represents. Not only can the graph style impact readers' interpretation of the graph (see for example Romano, Sotis, Dominioni & Guidi, 2020, and Schapira, Nattinger & McAuliffe, 2006), but the graph type that viewers are presented with may have "consequential impacts on judgement", as stated by Spiller, Reinholtz & Maglio (2019). Romano et al (2020) show that logarithmic data made graphical representations of Covid-19 data look less threatening, as the curve present in this type of graph is not as extreme as with linear data.

Studies have also shown that deceptive graph design is very powerful: Lauer and O'Brien (2020) found that deceptive graph design, involving techniques such as perspective shifting for pie charts, axis truncation for bar graphs and line graphs, and distance manipulation in bubble charts, impacted viewers' perceptions of the graphs: axis truncation and perspective manipulation caused a larger perceived difference between data points.

Axis truncation specifically is a technique that has been shown to strongly impact the perception of graphs in viewers, leading them to see the information as more dramatic, dangerous, or impactful. Pandey, Rall, Satterthwaite, Nov and Bertini (2015) investigated the effects of deceitful graph design in various ways, including axis truncation, inverted axes, presenting an area as quantity and distortion of the aspect ratio. Their study concluded that all of these methods had a significant effect on graph understanding and interpretation, in that the deceptive versions were more difficult to understand and often mislead the viewers in their interpretations.

These "deceptive" data visualizations – whether they are intentionally deceptive or not – are interwoven with the research presented so far. Firstly, graph type and style may significantly impact perception and liking of graphs, as Schapira et al (2006) found that participants in their study strongly preferred pictorial representations over bar graphs. This perception, in turn, may lead to increased or decreased attention and therefore, according to the Elaboration Likelihood Model, a difference in processing. Furthermore, intentionally deceptive graphs may require a more central processing route than non-deceptive graphs, as the first impression of the viewer may be skewed by the visual representation of the pure data. Therefore, it is possible that relevance and understanding are both affected by the type of graph style that is presented to the viewer.

This particular paper chooses to focus on the relationship between personal relevance, visual representation (in particular focusing on the differentiation between stock and deceptive stock graphs) and understanding. It aims to investigate whether personal relevance (in this case, related to location) as well as the type of visual representation of the data affects whether readers correctly interpret graphs about COVID-19 and their interpretation of those graphs.

Based on the literature discussed above and the Elaboration Likelihood Model, the research question for this paper in particular will therefore be: “To what extent do personal relevance and visual manipulation, as well as a combination of the two factors, affect understanding and perception of graphs?”.

As for the specific effects that can be expected, it can be assumed from research discussed that a high relevance will positively impact both understanding and perception of visual information. Similarly, it can be expected that a non-deceptive graph design will be easier to interpret and therefore increase understanding. The effects of deceptive graph design are tentatively phrased in the following section, because no clear direction can be assumed: it is possible that graphs that are perceived as easier are also perceived as more visually appealing, amounting to a positive influence on graph perception.

On the other hand, it is possible that exaggerated graphs are more attention-grabbing and look more interesting, which would result in better perception scores for deceptive design.

The hypotheses of this study are therefore the following:

H1: A higher relevance will lead to a better understanding of visual data.

H2: A non-deceptive graph design will lead to a better understanding of visual data.

H3: A combination of high relevance and non-deceptive graph design will lead to a better understanding of visual data.

H4: A higher relevancy will lead to a more positive perception of visual data.

H5: A non-deceptive graph design will have an effect on the perception of visual data.

H6: A combination of a high relevance and non-deceptive graph design will have an effect on the perception of visual data.

The method chosen for investigating this matter was an experimental study involving information about Covid-19 cases that was manipulated both in its visual form (presenting some participants with a deceptive version of the graph) and in its relevancy (presenting different background information regarding the location where the data was collected). Following these graphics, participants were asked to answer questions involving understanding, perception, and general graph literacy.

Methodology

This study was conducted in collaboration with other students from Radboud University and as such will include questions in its survey that are not relevant to this particular research paper (pertaining for example to decision making), but that will still be provided in the appendix.

Participants

The sampling and procedure that was employed consisted of mostly snowball sampling. Therefore, most of the participants were young adults from the Netherlands with a fairly high educational background. In total, 170 participants were included in the analysis.

The participants were recruited via online communication tools such as WhatsApp and Instagram and provided with a link to fill out a survey that was designed with the tool Qualtrics. Each participant was asked to fill out personal information at the beginning of the procedure (in order to exclude people under the age of 18) and was automatically assigned one condition of the experiment. The mean age of participants was 28.1, with the maximum age being 66 and the minimum age being 18. 105 participants identified as female, 63 as male, and one participant each selected the options for “I’d rather not say” and “Other”.

The general educational level of participants was high; only 29 participants had only a high school education.

Before beginning the survey, we asked for demographic information such as age, education level and gender, in order to ensure that the groups taking part in the different conditions would be sufficiently comparable. Participants who did not meet certain conditions (such as not living in the Netherlands or those who had not completed the survey) were removed from the sample. Participants had the choice to take the questionnaire in either English or Dutch, 29 participants chose to take it in English.

Participants were not financially compensated for their participation in the survey.

Materials

The independent variables that were manipulated in this study were relevance and visual representation of data.

Relevance was operationalized by customizing the data shown to the participants by country: The participants were shown either a graph that pertained to a location of high relevance for them (the Netherlands) or a graph that pertained to a location of lower relevance for them (Zambia). Therefore, the variable "relevance" has two levels, namely "high" and "low". It is important to emphasize at this point that the data we presented them with was fictional and did not represent the actual COVID cases in the Netherlands or Zambia. Ensuring that the participants were aware of this was crucial so that other factors (such as "it was Christmas two weeks ago, so there will be more cases") would not impact their interpretation of the data.

Relevance was measured as an ordinal variable.

Manipulation checks for relevance were included in the form of several 7-point Likert scales in order to assess whether the manipulation performed actually caused a perceived difference in relevance within the different conditions. This was assessed with the statements "The graph I saw is very relevant to me personally", "The positive Covid-19 tests in [country] are very relevant to me personally" and "The Covid-19 regulations in [country] are very relevant to me personally". This manipulation check was be conducted after the other questions had been answered. These manipulation checks were based on the work of Frewer, Howard, Hedderly & Shepherd (1997), who investigated relevancy in consumer research.

The internal reliability of the manipulation checks was sufficient at $\alpha = .8$.

Visual representation of data was operationalized by showing one of three different versions of graphs to the participants: one that depicts COVID cases in the particular location as a stock representation or a stock representation that was manipulated in order to deceive the participants. No numbers were changed, and the data remained exactly the same, but the graphical representation had the goal to make the situation look more dramatic than the non-manipulated stock graph did. This process was completed by the research team in accordance with the classification of deceptive graph visuals by Pandey et al (2015), whose study showed that axis truncation lead to significant differences in interpretation in accordance with the manipulation in their participants.

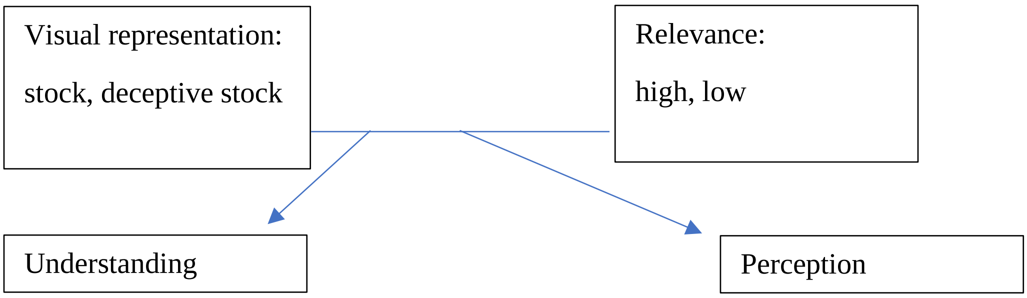
Visual representation was assessed with two levels and was also measured as a nominal variable.

Design

Given that there are two levels for relevance (high and low) and two conditions for visual representation (stock, flow, and deceptive stock), the design of this study is a 2x2 between-subjects design.

The analytical model of this study as a whole contains the following (for a complete version including the conditions not analysed in this paper, see the appendix):

Fig. 1: Analytical Model



Instrumentation

The dependent variables in this study are understanding and perception, all of which were assessed with scale questions (apart from some of the understanding questions) in a survey after the participants have had the opportunity to observe the visual data.

Understanding will be measured by asking the participants several questions about the first and second level of understanding of the data they are being presented with in accordance with Friel et al (2001), as well as Wainer (1992), both of whom identify three levels of graph understanding: An elementary level of understanding, which implies that the reader is able to extract singular data points from a graph; an intermediate level, which poses that the reader is able to identify general trends in the data, and an advanced level, which proposes a deeper understanding of the data, including being able to predict further trends and being able to group values that are present in the visual data.

The elementary level of data understanding was investigated by asking the reader to answer several questions about singular data points, e.g., “How many new COVID cases appeared on March 4th, 2021?”. The participants were asked to fill in open questions for these questions.

The intermediate level of data understanding will be investigated by asking the reader to answer questions about periods of time during the case development, e.g., “During which time period was the increase in COVID cases the highest?”. These questions were assessed with multiple-choice questions as well as with open questions.

The advanced understanding level was not assessed, as the assessment of this understanding would have essentially been a repetition of the decision-making question. It was therefore decided to not inquire further about the ability to make future predictions based on the data.

Depending on how many questions the readers answer correctly, a total score for understanding was calculated. Understanding was assessed as a ratio variable (as it is quantifiable and technically possible that there is no understanding whatsoever).

Details on the coding procedure regarding what was marked as “correct” and “incorrect” can be found in the appendix.

Furthermore, general graph literacy will also be measured. Similarly to the understanding questions, the graph literacy questions aimed for assessing both simple reading skills as well as more complex graph reading skills. These questions were posed at the end of the survey and asked participants to answer questions about other, simple graphics that they had not seen before. These graphics also related to health communication, and featured multiple different types of visual representation, such as pie charts and line graphs. These questions were based on the work of Galesic & Garcia-Retamero (2011).

Perception will be measured by asking the participants questions about their relative liking of the graph, using 7-point Likert scales. In this way, it will be possible to assess whether participants found a particular graph easy or difficult to read and whether they found the representation visually appealing. These questions, although they seem not as central as understanding, are crucial – in daily life, readers will look at graphs that they think are either useful or relevant to them, or graphs that are visually appealing. We are basing our questions on Bruine de Bruin, Stone, MacDonald Gibson, Fischbeck & Baradaran Shoraka (2013).

Thus, a short section was added to the questionnaire, posing three questions using semantic interval scales, one of which asked about graph clarity (“How clear was the graph that you saw?”), one of which asked about the ease of understanding (“How well did you understand the information you were given?”), and one of which asked about graph liking (“How much did you like the graph that you saw?”). All three questions had answer options ranging from “Not at all” to “Very”. All three of these questions were measured at the interval level.

The reliability of the perception variable was acceptable: α = .76.

This study included a third dependent variable, decision making. It was assessed by asking the participants a question about whether they would support certain measures to contain the spread of the virus in the following format: “The authorities of [country] are supposed to make a decision about whether they should reopen nonessential shops or whether they should prolong the closing of nonessential shops for another 14 days. Based on the graph you are seeing, what would your advice be?” The question was presented on a 7-point Likert scale, featuring options such as “Definitely reopen”, a neutral option and “Definitely stay closed”. These analyses will not be part of this paper and will not be discussed further.

All questions were constructed in English first and then translated to Dutch by native speakers.

Procedure and ethical concerns

The questionnaire was distributed via Qualtrics and developed within the group of students from Radboud University.

Each participant was provided with one graph and, after being given sufficient time to assess the graphs, was asked to answer the questions relating to perception, decision making and understanding, starting with decision making, as the other questions might influence the participants’ answers about decision making. After the understanding questions, they were asked to answer the questions pertaining to graph perception. They were also asked to answer some general questions about graph literacy based on different graphs; this section was structured similarly to the questions about understanding.

The participants were able to see the graph provided to them at any point during the questionnaire where the graph was relevant. The participants had as much time as they wanted to fill in the questions. The median response time was about 7 minutes.

As this research falls under “standard evaluation and attitude research”, the participants were not informed before filling out the questionnaire that relevance and visual representation of information are relevant concepts. They do, however, have the right to obtain more information from the students carrying out the study and an explanation of the graphs (especially in the deceptive condition) was provided. However, as the data is fictional, we do not expect any consequences to follow from the deception.

The questionnaire only recorded the information of participants anonymously, and participants had the right to stop taking the questionnaire at any point.

Statistical analyses and hypotheses

Before conducting analyses, participants under the age of 18 were automatically excluded by the Qualtrics algorithm and participants not living in the Netherlands were removed from the data set. As mentioned above, the three variables assessing perception were combined into one general variable, as well as the three questions pertaining to the manipulation checks for relevance. One participant was removed due to a response time that was considered too short to answer all questions carefully.

Given that this particular article assessing the study will analyse the effects of relevance and deception on understanding and perception of graphs, the statistical treatment of these questions will include two-way ANOVAs, as well as t-tests, to assess the differences between the low relevance/deception, high relevance/deception, low relevance/stock and high relevance/stock groups.

Furthermore, the same will be done to assess the effects of visual representation on understanding and perception.

These analyses would also make it possible to assess general differences between the high- and low relevance groups, as well as between the deception/no deception groups in regard to understanding.

The statistical effects tested for this article will be the following: a main effect of relevance on understanding (based on the Elaboration Likelihood Model), a main effect of visual representation on understanding, based on the research by Pandey et al (2015), as well as an interaction of visual representation and relevance on understanding. Adding to that, testing will be conducted for a main effect of relevance on perception, a main effect of relevance on understanding and an interaction effect of relevance and visual representation on perception.

Results

Before conducting any analyses, Chi-Square tests were performed for age, gender, and educational level in relation to relevancy and visual representation in order to assess whether any unexpected distributions of age, gender or education were present in the conditions. None of the analyses showed a significant result.

Descriptive testing for mean scores of understanding and perception

General descriptive analyses of the mean scores for understanding and perception, depending on both relevancy and visual representation, can be found in the following figure.

In total, 48 percent of participants received the condition "high relevancy", and 52 percent received the condition "low relevancy". 51 percent of participants received the condition "stock graph", and 49 percent received the condition "deceptive stock".

Fig. 2: Descriptives for deception, relevancy, understanding and perception

Relevance	Visual representation	Mean understanding	SD understanding	Mean perception	SD perception
High relevancy	Stock	.77	.22	4.81	1.31
	Deceptive	.79	.19	4.35	1.39
	Total	.79	.21	4.58	1.37
Low relevancy	Stock	.77	.22	4.87	1.00
	Deceptive	.80	.19	4.84	.84
	Total	.78	.21	4.84	.92

Descriptive testing for graph literacy scores

General descriptive testing was conducted for the graph literacy questions as well, which yielded a result of a mean score of M = .92, SD = .11 (1.00 representing a perfect score).

Two-way univariate analysis of variance regarding relevancy, visual representation and understanding

In order to assess the effects of relevancy and visual representation on understanding, a two-way univariate analysis of variance was performed. The analysis showed no statistically significant results for effects of relevancy (F (1, 166) = <1, p = .885, visual representation (F (1, 166) = 1.17, p = .279) or any significant interaction between the two independent variables (F (1, 166) = <1, p = .880).

Two-way univariate analysis of variance regarding relevancy, visual representation, and perception

A two-way univariate analysis of variance was performed to test the effects of visual representation and relevancy on total perception of the graphs. The analysis showed no statistically significant results for relevancy (F (1, 166) = 2.38, p = .124), visual representation (F (1, 166) = 1.92, p = .168), or an effect of interaction between the two factors (F (1, 166) = 1.43, p = .231).

Independent samples t-test for relevancy and manipulation checks

In order to assess whether the manipulation of relevancy was successful, an independent samples t-test was performed.

The manipulation checks showed that the average perceived relevance for the non-relevant condition (M = 2.40, SD = 1.13) was lower than the perceived relevance for the relevant condition (M = 4.45, SD = 1.40).

The t-test showed a significant effect of relevancy on the manipulation checks, with a value of t (168) = 10.471, p = < .001.

Discussion

The main aim of this study was to investigate the effects of relevancy and visual representation on understanding and perception by depicting the same data in a deceptive and non-deceptive form, as well as manipulating the relevancy by changing the origin country of the data.

Concluding from the results shown above, both of our hypotheses (namely, that there is an effect of relevancy and visual representation on both perception and understanding) have to be rejected.

Since none of the analyses performed yielded any statistically significant results (also none which were not statistically significant, but close to being significant), one has to discuss why this might be the case.

Starting with the effects of deception on understanding, there are several factors that may account for the differences in our results when comparing them to previous literature.

Evergreen & Metzner (2013) posed that simplicity, a reduced amount of information and a clear structure aid in graph understanding. Both of the graphs presented to participants in this study were designed to be very clear, simple and minimal in terms of the information they presented. This choice was made in order to exclude effects of unintentional increased complexity or a higher amount of information in one of the graphs, however, it is possible that the graphs were designed in a manner that made them too easy to read and understand, creating a floor effect. This possibility would be supported by the mean understanding scores, which were all fairly high and had little deviation, indicating that the graphs were generally easy to read.

It is also important to mention that we asked the participants to read and deduce exact numbers from the graphics, which likely made them pay a significant amount of attention to the graph's setup and details. Studies on deceptive visualization such as Lauer and O'Brien (2020) as well as Pandey et al (2015) largely focus on a broader kind of deception; in which participants do not explicitly misread the graph but interpret it wrongly at first glance. It is possible that the participants in this study may have thought the deceptive graph looked more “extreme” at first, as suggested by previous literature, but the closer examination mitigated that effect.

The lack of an effect of relevancy on understanding can be explained with a similar proposal: That close examination of the graphs and a high amount of attention was necessary and thus mitigated the effects of lower relevancy.

This could also be substantiated by the research provided by Petty & Cacioppo (1968): It is possible that due to the experimental setting and the explicit instructions, the participants processed all content via the central route, which then could lead to smaller differences in understanding than a situation in which some graphics would have been processed via the peripheral route. Since participants indicated via the manipulation checks that the Covid-19 cases in Zambia were less relevant to them than the ones in the Netherlands on average, it is unlikely that Zambia and the Netherlands were perceived as being equally relevant.

Therefore, the absence of an effect between relevancy and understanding as well as between graph type and understanding is explainable.

However, the lack of an effect on perception is less clearly explained: Prior research shows that relevancy clearly affected graph liking in studies such as Peck et al (2019). Naturally, it is possible that the sample size of this study was not large enough. However, there are alternative explanations that can be seen as exemplars of some of the difficulties surrounding this area of research.

Firstly, it is possible that perception and understanding are linked. Studies like Peck et al (2019), as well as Bucher & Schumacher (2006) pose that graphs that are easier to understand are also more well-liked and perceived as more pleasing, clear and attractive. Therefore, it is possible that the same floor effect that was mentioned as a possible reason for the lack of effects on understanding also plays into the lack of effects on perception: if graphs are very simple and clear, there is not much that can vary in viewers’ perceptions of them. This may also explain why the perception scores for the different graph visualizations were very similar,

Furthermore, the factor of choice and active selection may play a role. The study by Peck et al (2019) crucially employed a very different setting than this study: the participants were asked to choose graphs from an array of graphics, charts and tables and asked which ones were the most appealing to them. There are two aspects in this scenario that may fundamentally change the way that the participants saw the graphs: firstly, there was no obligation to interact or even look at any of the graphics. The participants did not have to answer questions about graphs that did not appeal to them, and there was no understanding element to the study. Secondly, the participants had the chance to compare the graphics against each other and then decide which ones they liked, whereas in this study, they were confronted with one single graphic that they had to interact with.

These potential explanations may apply to the concept of relevance itself; it is very difficult to create an experimental setting in which participants genuinely interact with graphics and visual material the same way they would in a non-experimental setting. As was already mentioned in the introduction, a non-relevant graphic will potentially not receive any attention at all if the viewer has the choice to ignore it in a realistic setting, but in an experiment, the viewer is forced to interact with the graphics, which may increase relevance. After all, even if the topic of a task may not be relevant to a particular person, if that task is their main focus in that moment, it may become naturally more relevant as there are no distractions or more relevant things present to focus on instead.

Naturally, there were also limitations in this study that could be improved upon in order to obtain better or more conclusive results, one of which has already been highlighted: the operationalization of relevancy is a very difficult endeavour, particularly when attempting to design an experiment that participants can partake in when in an online environment. It is possible that the operationalization applied in this study worked in theory, which would be supported by the manipulation checks, but did not transfer to the actual graphics. Whether participants did not focus on the country while processing the data or whether the relevancy for the lower-relevance condition increased because they were focusing on the understanding questions is ultimately unclear, but it is likely that the effects of relevancy were mitigated at least to some extent by the experimental setting.

A second issue is the participant group that was selected: 141 out of 170 participants pursued at least some kind of tertiary education. This highly educated group of participants is potentially less susceptible to deceptions in graphics and is most likely well-acquainted with graphics such as the one we chose, especially during a pandemic in which these types of graphs are referenced frequently and it is important to understand them. The graph literacy questions support this point, with a mean of .92, the scores for general graph literacy indicate that the participants were educated about graphics and knew how to interact with them. Therefore, a broader subject group would have likely represented the general population better and potentially would have yielded more diverse results.

Nevertheless, this study provides the starting point for more research into the topic of relevance and its link to understanding and perception of visual data. Despite the nonsignificant results of this study, there is potential in this area of research, and future investigations (ideally with more realistic settings) might be able to discover the conditions under which this connection is strongest. Suggestions for more appropriate settings could include in-person interviews, experiments which allow participants to choose a particular graphic that is most appealing to them, or even repeating this study with a more diverse group of participants in order to avoid the floor effects that were problematic in this particular paper.

In conclusion, though this study did not find any significant links between relevancy, visual representation, understanding and perception of health communication graphs about the Covid-19 pandemic, it is encouraged to do more research in this area, as the (relatively scarce) literature in this field suggests there might be a link between them in specific situations, which might benefit health communication, but could also be applied to other fields, such as marketing and science communication.

Bibliography

Bruine de Bruin, W., Stone, E.R., MacDonald Gibson, J., Fischbeck, P., & Baradaran Shoraka, M. (2013). The effect of communication design and recipients' numeracy on responses to UXO risk, *Journal of Risk Research, 16* (8), 981-1004

Bucher, H. & Schumacher, P. (2006). The relevance of attention for selecting news content. An eye-tracking study on attention patterns in the reception of print and online media, *Communications, 31* (3), 347-368

Evergreen, S. & Metzner, C. (2013). Design Principles for data visualization in evaluation. In Azzam, T. & Evergreen, S. (Eds), *Data visualization, part 2. New Directions for Evaluation, 140,* 5-20

Friel, S.N., Curcio, F.R. & Bright, G.W. (2001). Making sense of graphs: Critical Factors Influencing Comprehension and Instructional Implications, *Journal for Research in Mathematics Education, 32* (2), 124-158

Frewer, L.J., Howard, C., Hedderley, D. & Shepherd, R. (1997). The Elaboration Likelihood Model and Communication about Food Risks. *Risk Analysis, 17* (6), 759-770

Galesic, M. & Garcia-Retamero, R. (2011). Graph literacy: A cross-cultural comparison. *Medical Decision Making, 31* (3), 444-457

Glazer, N. (2011). Challenges with graph interpretation: a review of the literature, *Studies in Science Education, 47* (2), 183-210

Lauer, C & O'Brien, S. (2020). How People are influenced by deceptive tactics in everyday charts and graphs. *IEEE Transactions on Professional Communication, 63* (4), 327-340

Okan, Y., Stone, E.R. & Bruine de Bruin, W. (2018). Designing Graphs that Promote Both Risk Understanding and Behaviour Change. *Risk Analysis, 38* (5), 929-946

Pandey, A.V., Rall, K. Satterthwaite, M., Nov, O. & Bertini, E. (2015). How deceptive are deceptive visualizations? An empirical analysis of common distortion techniques, *New York University Public Law and Legal Theory Working Papers*, paper 504

Peck, E.M., Ayuso, S.E. & El-Etr, O. (2019, unknown day). Data is personal: Attitudes and Perceptions of Data Visualization in Rural Pennsylvania [Conference presentation]. CHI ’19: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, Glasgow, Ireland.

Petty, R.E. & Cacioppo, J.T. (1986). The Elaboration Likelihood Model of Persuasion, *Advances in Experimental Social Psychology, 19* (1), 123-205

Romano, A., Sotis, C., Dominioni, G. & Guidi, S. (2020). The scale of COVID-19 graphs affects understanding, attitudes and policy preferences, *Health Economics, 29* (11), 1482-1494

Schapira, M.M., Nattinger, A.B. & McAuliffe, T.L. (2006). The Influence of Graphic Format on Breast Cancer Risk Communication, *Journal of Health Communication, 11* (6), 569-582

Shah, P. & Hoeffner, J. (2002). Review of Graph Comprehension Research: Implications for Instruction, *Educational Psychology Review, 14* (1), 47-69

Sher, P.J. & Lee, S. (2009). Consumer skepticism and online reviews: An Elaboration Likelihood Model Perspective, *Social Behaviour and Personality: an international journal, 37* (1), 137-143

Spiller, S.A., Reinholtz, N., & Maglio, S.J. (2019). Judgements based on Stocks and Flows: Different Presentations of the Same Data Can Lead to Opposing Inferences, *Management Science; Articles in Advance*, 1-19

Teeny, J., Briñol, P. & Petty, R.E. (2017). *The Elaboration Likelihood Model: Understanding consumer attitude change.* In C.V. Jansson-Boyd & M.J. Zawisza (Eds.), *Routledge international handbooks. Routledge International handbook of consumer psychology* (p. 390-410). Routledge/Taylor & Francis Group

Wainer, H. (1992). Understanding Graphs and Tables, Educational Testing Service [Conference presentation]. Annual Meeting of the American Educational Research Association, 1991, Chicago, IL, United States.

Appendix

Fig.3: Elaboration Likelihood Model by Petty & Cacioppo (1986)

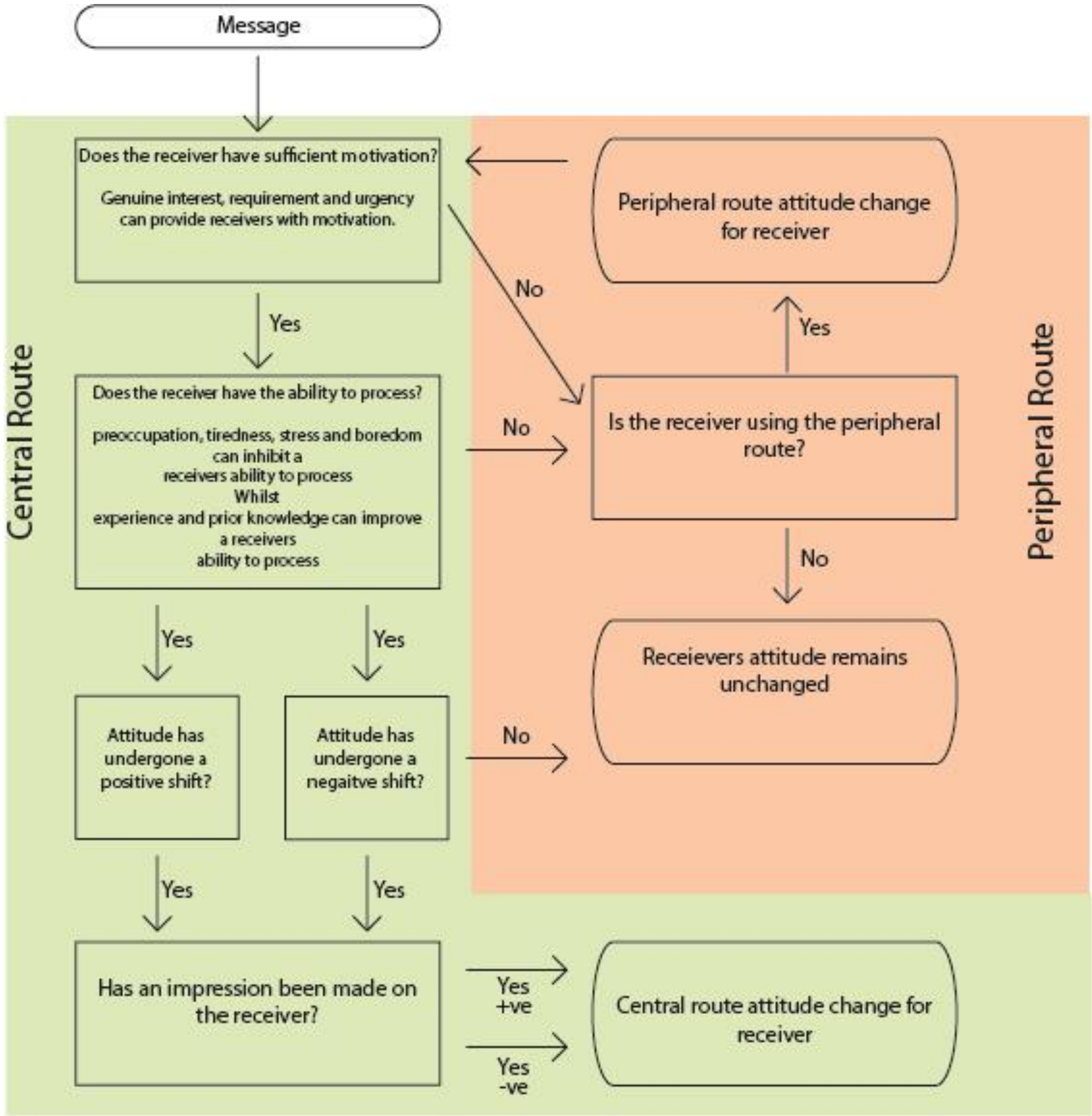


Fig. 4: Analytical Model (complete version)

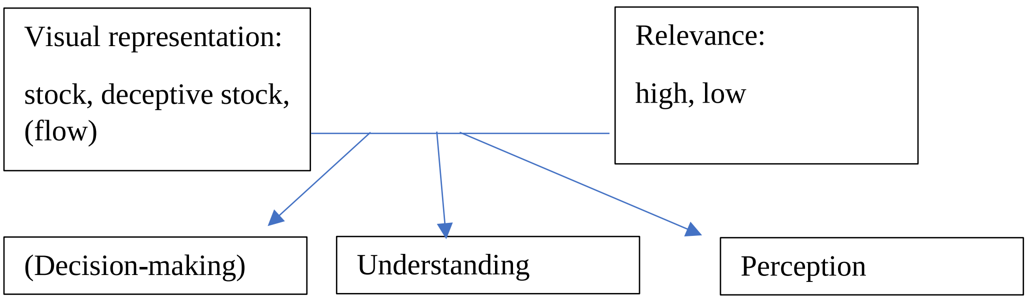


Fig. 5: non-deceptive stock graph

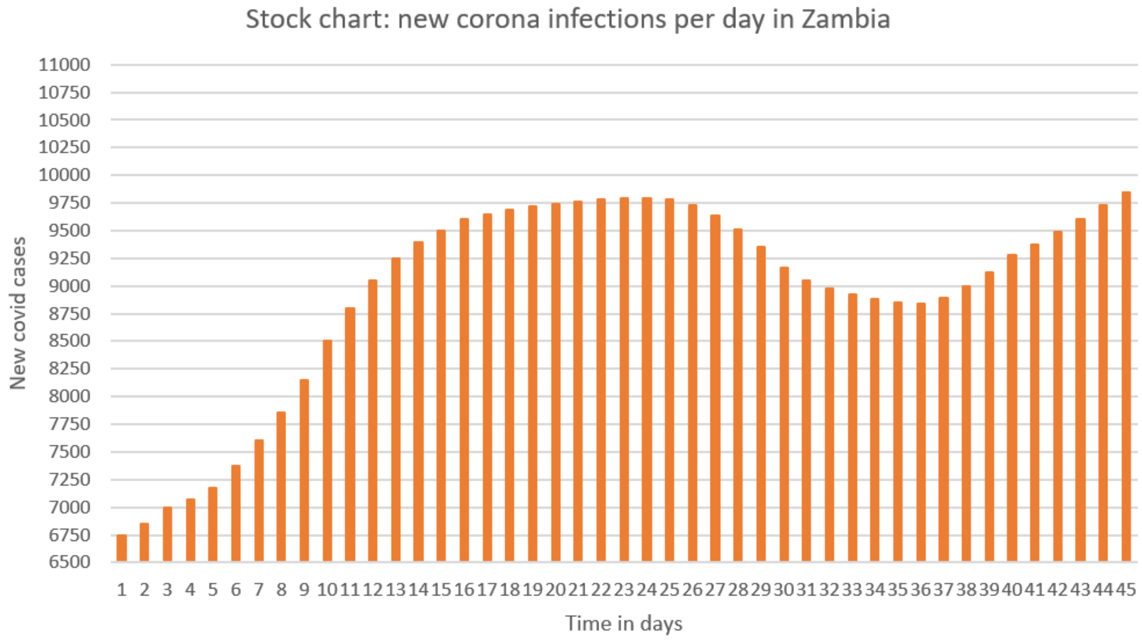
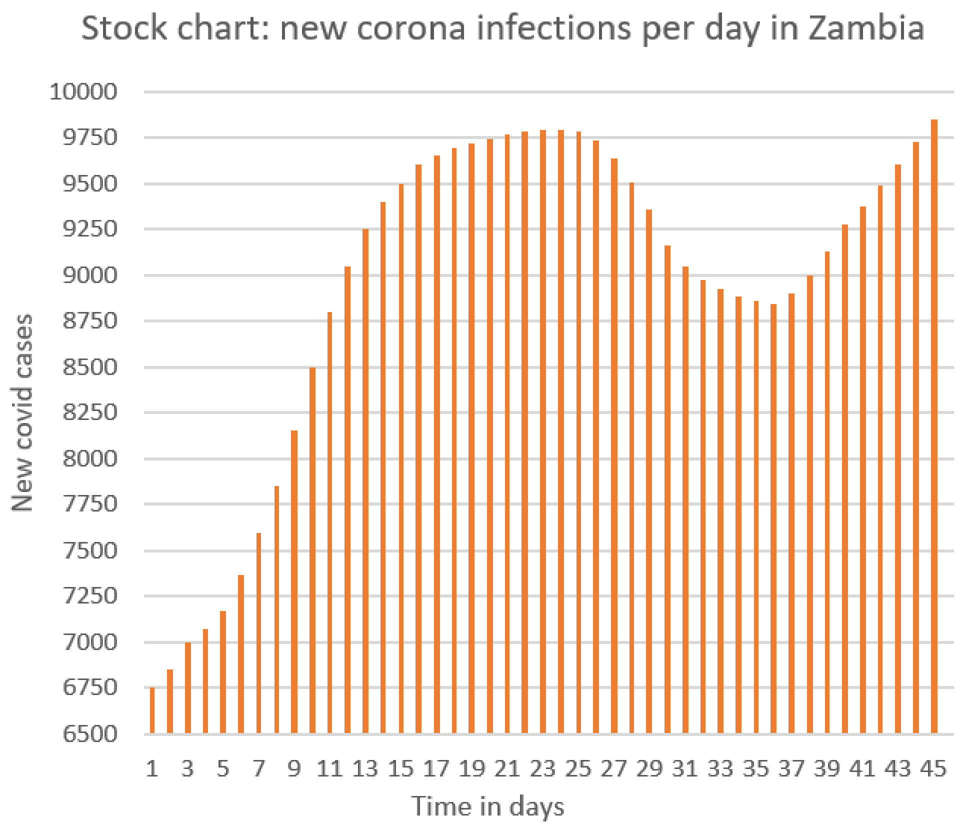


Fig. 6: deceptive stock graph



Questionnaire summary:

1. Metadata

   In which country do you live? (Options: Netherlands / Other)

   How old are you?

   What is your gender? (Options: Man / Woman / Other / I'd rather not say)

   What is your current or last completed educational level? (Options: Primary School / High School / Trade School / University of Applied Sciences / Bachelor / Master /PhD

2. Decision-making

   The following stock graph depicts fictional data about the number of new corona infections for each day in [country].

   The authorities of [country] are supposed to make a decision about whether they should reopen the nonessential shops or whether they should prolong the closing of nonessential shops for another 14 days. Based on the graph you are seeing, what would your advice be? (Options: 1-7, 1 = Definitely stay closed, 7 = Definitely reopen)

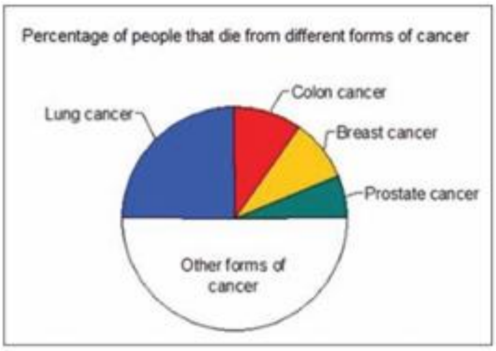
3. Understanding
   How many new covid cases were registered on day 3? (Open question, 6800-7200 was coded as correct)
   Look at day 3 and day 4. Which day shows the biggest increase in new infections compared to the day before? (Options: Day 3 / Day 4, Day 3 was coded as correct)
   Compare the period from day 1 to day 10 to the trend from day 11 to day 20. Which trend shows a stronger rise in infections? (Options: 1-10 / 11-20, 1 to 10 was coded as correct)
   What is the difference in the number of new infections between day 12 and 13? (Open question, values between 160 and 240 were coded as correct)
   On which day did the decrease of covid-19 infections begin to slow down? (Open question, values between 30 and 32 were coded as correct)

4. Manipulation check relevancy
   The graph I saw is very relevant to me personally (7-point scale, 1 = Strongly disagree, 7 = Strongly agree)
   The positive Covid-19 tests in [country] are very relevant to me personally (7-point scale, 1 = Strongly disagree, 7 = Strongly agree)
   The Covid-19 regulations in [country] are very relevant to me personally (7-point scale, 1 = Strongly disagree, 7 = Strongly agree)

5. Perception
   How well did you understand the information you were given? (7-point scale, 1 = Not at all, 7 = Very well)
   How clear was the graph that you saw? (7-point scale, 1 = Not clear at all, 7 = Very clear)
   How much did you like the graph that you saw? (7-point scale, 1 = Not at all, 7 = Very much)

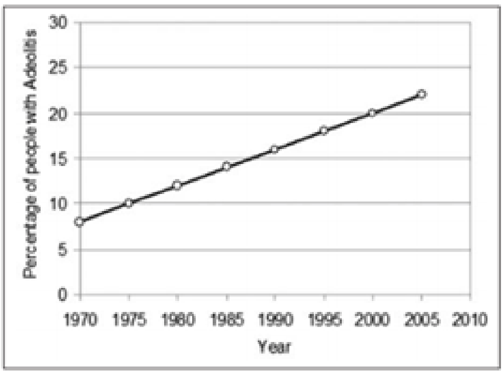
6. Graph literacy

Fig. 7: pie chart regarding cancer forms, graph literacy question 1



Out of all the people who die from cancer, approximately what percentage dies from lung cancer? (25% was coded as correct)

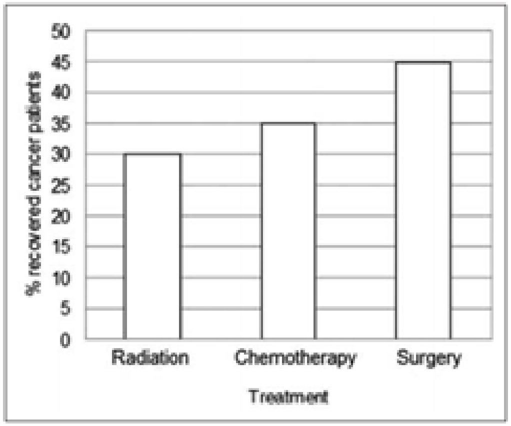
Fig. 8: line graph regarding Adeolitis rates, graph literacy question 2 and 3



Approximately what percentage of people had Adeolitis in the year 2000? (20 was coded as correct)

When was the increase in the percentage of people with Adeolitis higher? (Options "1975-1980", "2000-2005", "Increase was the same in both intervals", "I don't know", "It was the same in both intervals" was coded as correct)

Fig. 9: recovery rates regarding cancer treatments, graph literacy question 4 and 5



What percentage of the patients recovered after chemotherapy? (35% was coded as correct)

What is the difference between the percentage of patients who recovered after a surgery and the percentage of patients who recovered after radiation therapy? (15% was coded as correct)

Appendix A. Statement of own work

Sign this *Statement of own work* form and add it as the last appendix in the final version of the Bachelor's thesis that is submitted as to the first supervisor.

Student name: Lucie Gobbels

Student number: s1016341

PLAGIARISM is the presentation by a student of an assignment or piece of work which has in fact been copied in whole or in part from another student's work, or from any other source (e.g. published books or periodicals or material from Internet sites), without due acknowledgement in the text.

DECLARATION:

a. I hereby declare that I am familiar with the faculty manual (https://www.ru.nl/facultyofarts/stip/rules-guidelines/rules/fraud-plagiarism/) and with Article 16 "Fraud and plagiarism" in the Education and Examination Regulations for the Bachelor's programme of Communication and Information Studies.

b. I also declare that I have only submitted text written in my own words

c. I certify that this thesis is my own work and that I have acknowledged all material and sources used in its preparation, whether they be books, articles, reports, lecture notes, and any other kind of document, electronic or personal communication.

Signature:

Place and date: Nijmegen, 03/06/2021