Visualising Climate Action Urgency: Inclusive Data Communication

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Abstract

Human-induced global warming drives climate extremes across the entire globe. Thus, people need to understand the consequences of already accumulated CO2, and why reaching the net-zero CO2 emissions has to be achieved as soon as possible. A communication tool that has power to spread the environmental awareness is data visualisation. The current research aims to find empirical evidence for the effects of three design guidelines (shade, annotations, animation) applied to carbon emissions scenario figures on following outcome measures: climate change risk perception, climate beliefs, climate policy support and real-world action. By testing different ways of visualising the carbon emission figures, we investigated how best to visualise data to convey the message concerning the urgency of taking a climate action due to cumulative impact of CO2. We expected people exposed to visualisations including the most cognitive cues (e.g. annotations) to score highest on the outcome measures. The final sample consisted of 314 non-climate scientists, who were randomly assigned to eight experimental groups and one control group. Our results did not show any effects of the chosen design techniques on any of the outcome measures. The main limitation of this study is a small and homogenous sample. We also concluded that there is some vagueness in the literature concerning how data visualisation design guidelines should be applied. Future research should focus on specifying the data visualisation guidelines and their application, as well as investigating user-cantered and transdisciplinary approaches to improve climate data communication to all types of audiences.

Keywords: data visualisation, graph literacy, climate change, carbon emissions, climate action

Layman's Abstract

Human-induced global warming drives climate change, resulting in phenomena such as droughts and tropical cyclones. Similar to filling a bathtub with water, our atmosphere steadily accumulates CO2 emissions. Just as stopping the flow does not immediately empty the tub, halting emissions will not swiftly clear the atmosphere of CO2. Hence, people need to understand the consequences of already accumulated CO2 and why reaching the net-zero CO2 emissions must be achieved urgently. A communication tool that has the power to spread environmental awareness is data visualisation. This research was aimed at finding empirical evidence for the effects of three design guidelines (shade, annotations, animation) applied to carbon emissions scenario figures on following outcome measures: climate change risk perception, climate beliefs, climate policy support and real-world action. By testing different ways of visualising the carbon emission figures, we investigated how best to visualise data, using the existing knowledge, to convey the message concerning the urgency of taking a climate action due to cumulative impact of CO2. We expected that participants exposed to visualisations with the most design dimensions applied (e.g. annotations) to score highest on the outcome measures. We gathered a final sample of 314 non-climate scientists, who were randomly assigned to eight experimental groups and one control group. The results did not show any effects of the chosen design techniques on the outcome measures. Future research should focus on specifying the data visualisation guidelines and their application to improve climate data communication to all types of audiences.

Keywords: data visualisation, graph literacy, climate change, carbon emissions, climate action

Introduction

The climate is changing rapidly resulting in phenomena such as heatwaves, heavy precipitation, droughts and tropical cyclones. The attribution of those extremes to human influence has strengthened over years (IPCC, 2022). AR6 is a summary of the three previous IPCC reports and it emphasises the role of human-induced global warming in driving those climate extremes across the entire globe. As Christiana Figueres said, “we must finally understand serious existential consequences resulting from not changing our attitudes” (Carrington, 2021). Therefore, a radical social transition is necessary for people to understand the consequences of already accumulated CO2 and why reaching the net-zero CO2 emissions has to be achieved as soon as possible.

Net-zero by 2050 has been a focal point for corporations and governments. However, it made people forget that it is not reaching this “deadline” that matters, but the journey toward it: the total, i.e. cumulative, amount of CO2 that we emit over time (Net Zero Is a Race, Not a Destination, 2022). Once CO2 is released it can stay in the atmosphere between 300 to 1000 years, meaning that CO2 released today will endure the timescale of many human lives (Buis, 2019). This is the reason why the total amount of emitted CO2 should be considered while predicting, for instance, the temperature rise.

However, the misconception that people often have is that reaching the net zero pledge will make all of the gas we have emitted along disappear (Net Zero Is a Race, Not a Destination, 2022). This issue was stressed by a Dutch Fossil Free Coalition activist, Hiske Arts, who contributed to this research. According to her own observation, the general public struggles with understanding that reaching the carbon net-zero pledge does not eliminate the already accumulated CO2 emissions in the atmosphere.

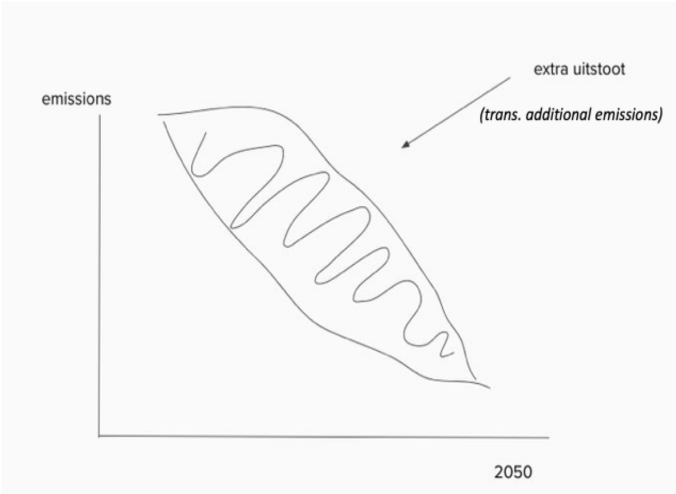
Depending on the total amount of accumulated CO2 by the time the net-zero target is reached, different climate scenarios would be faced by humanity and the entire planet. Existing data suggests that current public engagement with climate is low and the issue is often perceived as distant in time and space (Hagen et al., 2015; Pidgeon & Fischhoff, 2011). Therefore, the ultimate goal is to shift from 'end-point' thinking to 'total cumulative impact' thinking.

This societal issue indicates that there is a huge demand for communication tools, which could spread environmental awareness and improve understanding of the current climate action urgency. One of such tools is data visualisation. This tool is essential in the communication of current climate change findings and future climate change predictions to both expert and non-expert audiences (Harold et al., 2016). However, many graphics are still aimed at experts, making it difficult for non-experts to understand them (McMahon et al., 2015). Thus, the full potential of data visualisation, in terms of the size of audience it could potentially reach, is often not met. Of course, a good display design cannot compensate for lack of relevant knowledge, but it can definitely help to make task-relevant information salient and eliminate irrelevant information (Hegarty, 2011).

Therefore, the explicit goal of this study is to investigate how the full potential of climate data visualisation could be met. To achieve that, our study examines whether exposure to figures designed based on guidelines extracted from the scientific literature could change people's attitude towards climate change. We aimed to achieve that by using cognitive cues that were supposed to stimulate the 'total cumulative' thinking in people exposed to data visualisations designed by us. Hiske Arts provided us with a provisional drawing, which became our design's baseline (Figure 1).

Figure 1.

Hiske Art's sketch shows that there is a big difference between various pathways that all lead to a net-zero 2050 endpoint.



It resulted in an internship project that preceded this master thesis research. The purpose of that internship was designing climate scenario figures, with application of guidelines extracted from the literature. Figures designed by us are supposed to emphasise the consequences of the total carbon budget and be accessible for a non-expert audience (i.e. non-climate scientists). The designed figures are differentiated across three design dimensions extracted and inspired by the scientific literature. Each dimension consists of two levels: shade (shade/no shade), annotations (annotations/no annotations) and guided animation (animation/no animation). Reasons for choosing these design dimensions are described in the following paragraphs (for the summary see Table 1).

According to Padilla et al., (2022) people's risk perception is higher when they look at cumulative graphs compared to instantaneous data graphs. Additionally, an NGO activist Hiske Arts, who participated in the current project, shared concerns regarding the general public not understanding when a cumulative data graph and an instantaneous data graph convey the same message; more precisely, people do not understand that an area under an instantaneous data graph is equivalent to the cumulative data indicated by a point on the cumulative graph. Similar to filling a bathtub with water, our atmosphere steadily accumulates CO2 emissions. The same way stopping the flow will not immediately empty the tub, halting emissions will not swiftly clear the atmosphere of CO2. Shading an area of the instantaneous data graph in this project was an attempt to avoid this misconception. It is known that pre-attentive elements, such as colour or motion, can cause people to process information before they pay conscious attention to it (Terrado et al., 2022; Janes et al., 2013). Shading was used for that exact purpose; it marks the area under the graph and therefore, gives a cognitive cue indicating that the area of the instantaneous data graph corresponds to points on the cumulative data graph.

The use of annotations in this project was supposed to provide a narrative context and build emotional connectivity with the issue of climate change. Creating a narrative, or in other words storytelling, around the data visualisation is particularly important for low-knowledge readers, who cannot rely on prior experience to guide their attention as experts do (Franconeri et al., 2021). Research suggests that narrative formats are more engaging and easier to comprehend than traditional rationale-based approaches to science communication. Emphasising narrative within a visualisation allows users to create linkages with new knowledge and, in many cases, build emotional connectivity within the communication process (Grainger et al., 2016). On the other hand, in the wider visualisation community, there is a stigma that data visualisations should be "objective" (Lee-Robbins & Adar, 2022). For that reason, annotations used in this project are purely factual and based on IPCC's AR6. They do have an affective element; they mention big societal problems that can arise from the possible increase in global temperature in the upcoming years.

The idea of using animation was inspired by research on interactive graphs and their advantages and disadvantages compared to the static graphs. Studies comparing static graphics with animated graphics are often flawed due to the presence of additional information in the animated graphics. As a result, any advantages observed in animated graphics may not be solely attributed to animation itself (Harold et al., 2016; Tversky et al., 2002). In fact, animation may even hinder understanding in certain scenarios (Harold et al., 2016; Mayer et al., 2005). People may focus on the visually salient aspects of the animation, rather than the necessary information, leading to cognitive overload (Harold et al., 2016; Lowe, 2003; Lowe, 1999). In this project, however, a guided animation was used; the user observes the reveal of particular elements of the graphic step by step, so that the order in which particular elements should be paid attention to was established in advance. It is a way of scaffolding, as it navigates the order in which graphs should be viewed as a whole. In the study of Stofer and Che (2014), eye-tracking showed that with each type of scaffolding, the novices' paths started to resemble more closely the paths of the experts than in the unscaffolded case. The attempt of using guided animation as a form of scaffolding is supposed to reveal whether it could actually be a better approach towards graph design than using static graphs only.

Table 1

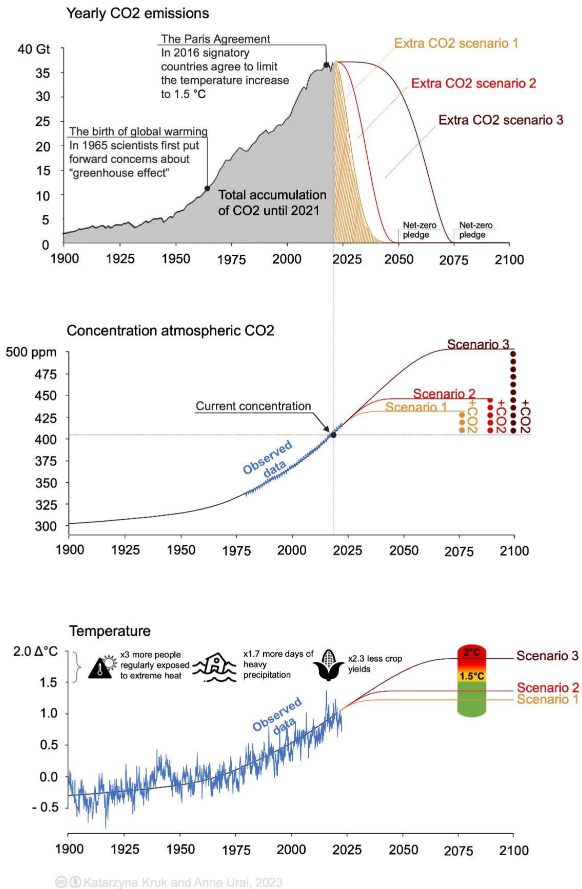
Design dimensions: summary

Design dimensions		
Annotations	Guided animation	Shading
○ Annotations create a narrative around the data visualisation. It is beneficial for low-knowledge readers, who cannot rely on prior experience to guide their attention as experts do (Franconeri et al., 2021). ○ Narrative within a visualisation allows users to create linkages with new knowledge and build emotional connectivity within the communication process (Grainger et al., 2016).	○ In this project a guided animation is used. It is a way of scaffolding; it navigates the order in which graphs should be viewed as a whole. ○ In the study of Stofer and Che (2014), the eye tracking data showed that with each type of scaffolding, the novices' paths started to resemble the paths of the experts more closely than in the unscaffolded case.	○ Pre-attentive elements (e.g. colour, motion) can cause people to process information before they pay conscious attention to it (Terrado et al., 2022; Janes et al., 2013). ○ In this project, shading marks the area under the graph and therefore, gives a cognitive cue indicating that the area of the instantaneous data graph corresponds to points on the cumulative data graph.

Given those 3 design dimensions, we decided to create 8 sets of graphs in order to investigate each dimension separately, as well as every possible combination of these dimensions. Due to the fact that the graphs were designed during the internship preceding this master thesis project, they were already shared with Hiske Arts. For an exemplary set of graphs see Figure 2.

Figure 2.

A static (not animated) set of graphs including two design dimensions: shade and annotations.



All other sets of graphs can be found at https://doi.org/10.5281/zenodo.7767084 (Kruk & Urai, 2023). By sharing newly designed sets of graphs under an open license, we contributed to Hiske's mission concerning clarifying misconceptions regarding the cumulative CO2 emissions and their consequences.

The purpose of this master thesis project is to take this mission even further and find empirical proof for the effectiveness of those visualisations. Though current scientific literature provides us with different design guidelines, there is a lack of studies which compare the effectiveness of different methods extracted from different scientific sources, as well as the effectiveness of combining those different methods within one design. How can we best visualise risk to communicate the urgency of the climate crisis? How can we use already existing knowledge on visualising data to communicate the urgency of taking climate action already today? The current study aims to find an answer to the question whether the accuracy of understanding data and the message it is supposed to convey can be optimised by means of applying techniques extracted from existing literature.

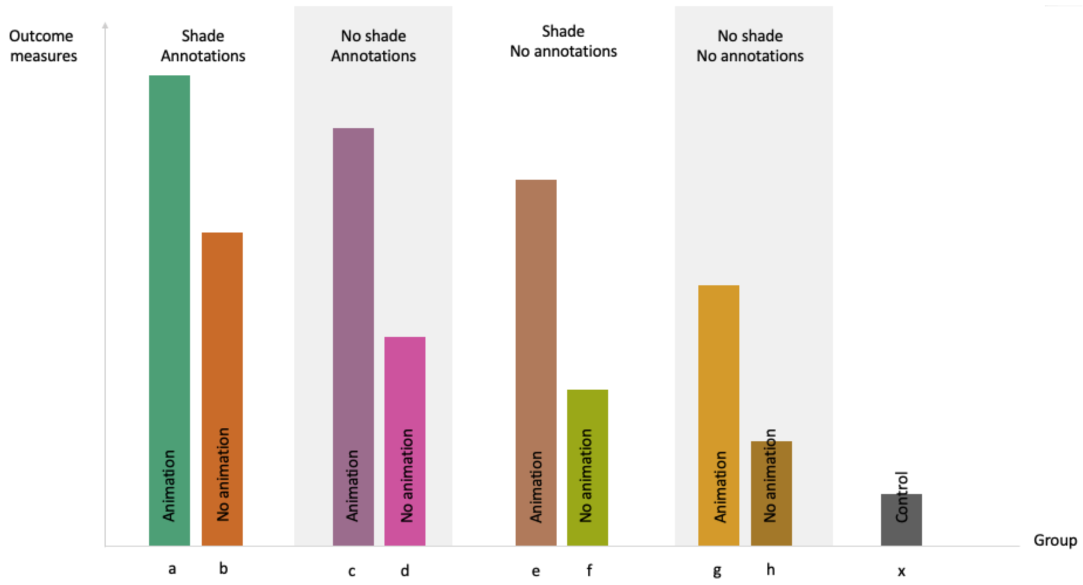
This study also aims to distinguish the most effective design principles for visualising specific climate scenario figures created by us. The design principles we applied to our visualisations are supposed to make the data easy to understand for the non-expert audience. In order to investigate the effectiveness of the chosen design techniques and to answer the research questions, we gathered 8 experimental conditions and 1 control condition. Each experimental condition was exposed to a different (combination of) data display technique(s).

Participants were asked to fill in questionnaires that investigate four outcome measures: their risk perception, climate beliefs, climate policy support, and real-world climate action. Additional variables were collected to assess participants' approach towards climate activism and graph literacy. The measures were mostly inspired by Vlasceanu et al. (2023), whose work is an example of psychology contributing to climate communication and intervention efforts.

The main objective was to examine and compare the separate effects, as well as interactions between all three design dimensions extracted from the literature (see Table 1), on the audience's risk perception, climate beliefs and policy support, and motivation towards climate action. Based on this 3-factor study design we extracted 3 hypotheses (Figure 3).

Figure 3.

Bar plot visualising hypotheses.



Firstly, all groups exposed to visualisations including guided animation will have higher risk perception and higher motivation to take and support climate action than groups that were exposed to visualisations not including animation. This hypothesis is based on the finding that scaffolding helps to guide the novice audience's gaze in a way resembling experts' gaze when they are exposed to a visualisation (Stofer & Che, 2014).

Secondly, all groups exposed to visualisations including annotations will have higher risk perception and higher motivation to take and support climate action than groups that were exposed to visualisations not including annotations. This hypothesis is based on the finding that annotations create a narrative which helps laypeople with creating linkages with the new knowledge and even build emotional connectivity with the presented issue (Franconeri et al., 2021; Grainger et al., 2016).

The third hypothesis predicts that visualisations including shade will have an effect on risk perception and motivation to take and support climate action, considering that it is a pre-attentive element leading the audience's attention to the area under the graph (Terrado et al., 2022; Janes et al., 2013). However, due to lack of stronger evidence in the literature, this hypothesis remains non-directional and exploratory.

Moreover, we also expect groups exposed to different combinations of the design dimensions to score higher on outcome measures compared to the group not exposed to any of the dimensions or their combinations. The rationale behind this hypothesis is that combining different design dimensions together could potentially decrease the cognitive load of recipients and hence, facilitate understanding of the message conveyed by the figures (De Jong, 2009).

We assessed the potential impact of various design dimensions (and their combinations), considering their efficacy as supported by existing literature that we found. Our assessment led to ordering the design principles from the one with supposedly the strongest impact, to the one with supposedly the smallest impact, as follows: animation, annotations, shade. The control group exposed to the climate change unrelated graph was expected to score lowest on the outcome measures compared to the rest of experimental groups.

Methods

Design

There are 3 independent categorical variables with 2 levels each: shade/no shade, annotations/no annotations and animation/no animation. The objective is to examine and compare the separate effects, as well as interactions between all three design dimensions. This results in 8 experimental groups and 2 x 2 x 2 between-subjects factorial design.

The 3 dependent ordinal variables include risk perception, climate beliefs and climate policy support. All these variables are measured by questionnaires consisting of scales. The last dependent variable is nominal and measures real world climate action. A questionnaire is used to collect this data.

Additional variables are collected to control for approach towards climate activism and graph literacy. Approach towards climate activism is an ordinal variable and it is measured on a scale. Graph literacy is an interval variable and it is measured by four multiple choice questions. Those variables are used as post hoc confounders to control for the alternative interpretations of results.

If participants score high on any of the described confounders, we expect them to be willing to take climate action and to score high on scale measures. Results could be then (partially) explained by our participants' baseline approach towards climate activism and/or their experience in reading graphs, rather than exposure to different data visualisations on its own.

Participants

Most participants were recruited through SONA and rewarded with 1 experiment participant credit (the experiment participant credits are a requirement for the Leiden undergraduate curriculum in Psychology and Pedagogic Sciences). We also found volunteers who participated in our study voluntarily and without obtaining any kind of compensation. This sample goes beyond university students and was obtained by sending the link to the study through different channels. The ratio of students and the rest of participants could be easily calculated by comparing the number of participants who completed the study through SONA (N = 260) and the number of participants who completed the study directly through Qualtrics (N = 112).

Our goal was to recruit a sample of 675 participants (around 75 participants per each of eight experimental conditions and one control condition). This is based on Padilla et al.'s (2022) study, who examined how COVID-19 visualisations influence risk perception. They based their sample sizes on prior research on decision making with visualisations as pilot data and calculated an anticipated effect size (pseudo r2 = 0.02; Padilla et al., 2022). Due to time restrictions of this master thesis project we managed to gather 372 participants in total (SONA = 260; Qualtrics = 112). We excluded 58 participants who did not complete the study and/or failed to complete the attention checks and/or completed them incorrectly. The final sample consisted of 314 participants (mean age: *M* = 22.9, *SD* = 7; females = 239, males = 59, other = 7, prefer not to say = 9).

Our sample included mostly participants from the general student population. Considering the homogeneity of such a sample, the potential target for the future research would be investigating climate interventions across global, more diverse populations.

All participants were provided with an information letter, they all provided informed consent and were debriefed at the end of the experiment. The study protocol was approved by the Psychology Research Ethics Committee (Institute of Psychology, Leiden University), with the approval code "2023-06-19-A.E. Urai-V2-4858". The sample for the current study was required to have sufficient understanding of written English as that the study was fully conducted in English.

Apparatus and measures

Risk perception was evaluated by using a scale from Dong et al. (2022), who provided evidence for the validity of this instrument in their previous study (i.e. Wang et al., 2021). The scale contains nine items (e.g. 'How concerned are you about global warming?') with a 4-point response format ranging from 1 (none) to 4 (very; see Appendix A). Higher scores indicate greater climate change risk perception.

Climate beliefs were measured by participants' answer to the question "How accurate do you think these statements are?" with the response format ranging from 0=Not at all accurate to 100=Extremely accurate (see Appendix B). The measure is taken from Many Labs' preregistered study about the effectiveness of climate action interventions (Vlasceanu et al., 2023).

Climate policy support was operationalized by measuring participants' level of agreement from 0=Not at all to 100=Very much so, with nine statements (e.g. 'I support raising carbon taxes on gas/fossil fuels/coal.'; see Appendix C). The measure is taken from Many Labs' study (Vlasceanu et al., 2023).

Real world climate action was assessed by measuring participants' willingness to share a climate related post on social media. Participants were asked to answer a question "Are you willing to share this information on your social media?", with the answer options being "Yes, I am willing to share this information", "I am not willing to share this information", and "I do not use social media". Participants who indicated they do not use social media were excluded from analysis related to that measure. The information participants received was: "Did you know that removing meat and dairy for only two out of three meals per day could decrease food-related carbon emissions by 60%? Source:

https://econ.st/3qjvOnn". Participants were asked to take a minute to publish the post. They were asked to answer yes/no to a question "Did you share the information?" (yes/no) and to indicate the platform (e.g., Facebook, Twitter, Instagram) on which they posted the information. Given that we considered that the willingness to share the social media post does not always have to result in the actual post sharing, the real-world action measure resulted in two separate variables: intention to share the social media post and actual sharing of the social media post. This is a simplified version of the ManyLabs' measure of the real-world climate action; they also used social media post sharing as a task (Vlasceanu et al., 2023).

In order to test for participants' graph literacy, they were asked to complete a graph literacy measure (4 question Graph Literacy measure; Okan et al., 2019; see Appendix D). By evaluating participants' graph literacy, we wanted to make sure that results of our outcome measures are not confounded by factors such as for example lacking the skill to read and understand graphs overall.

Additional variables, which were collected to assess participants' approach towards climate activism, were measured by a questionnaire also taken from the ManyLabs' preregistered study (Vlasceanu et al., 2023). Participants were asked to rate seven statements (e.g. 'On average, how competent are climate change research scientists?') with the response format ranging from '0=Not at all' to '100=Very much so' (see Appendix E). By evaluating participants' approach towards climate activism, we wanted to make sure that results of our outcome measures are not confounded by factors such as for example being strongly against climate action as a baseline.

Software used for conducting the study was Qualtrics. All questionnaires together took approximately 15 to 20 minutes to complete. We used JASP and SPSS for conducting the statistical analyses. R was used for some of the visualisations. Additional information, codes and figures are available at our GitHub repository (Kruk & Urai, 2023).

Procedure

The actual study was preceded by a small pilot, during which 10 volunteers were asked to complete the experiment. The goal was to make sure that the study runs as expected and all the instructions are clear to participants. The pilot resulted in minor changes of the order of the questionnaires. Implementing our volunteers' feedback allowed us to make sure that the study set up well and has a good flow in Qualtrics. After a successful pilot, the actual experiment took place in an online environment. All the procedures were conducted in Qualtrics. Participants were able to sign up through the SONA website or could access the study directly through Qualtrics.

Participants were first presented with an information letter which included essential information about the ethical approval of the study, conditions of participation, outline of the procedure, confidentiality and privacy policy, as well as contact information. Information letter was followed by the informed consent. Participants were allowed to quit the experiment at any moment without any consequences.

After signing a consent, participants could proceed with the study. To make sure that all the questions are answered we used a "force response" answering format in Qualtrics. The only exception to that answering format were two attention checks that we implemented in between questionnaires to check whether participants are paying attention to the experiment. The first attention check was in the form of a question "To indicate you are reading this paragraph, please select 'green' from the list below". In the second attention check we asked participants to type 'sixty' in an indicated typing box. Participants who skipped attention checks without giving any answers and/or gave incorrect answers were excluded from analysis.

The first questionnaire that participants were presented with was the 4 question Graph Literacy measure. This questionnaire was followed by the first attention check. After completing that section, participants were presented with an instruction: "In the next section you will see a graph. You have a minimum of 1 minute and 30 seconds to get acquainted with it, which means you will not be able to proceed to the next section before that time passes.”. After confirming they read and understood the instruction, participants were presented with a stimulus assigned to their group.

Groups in experimental conditions were differentiated by different combinations of independent variables: animation, annotations and shade. There are 8 possible combinations of those 3 variables, resulting in a total of 8 experimental groups. Participants in the active control condition were presented with an unrelated graph showing the increase of international students in the Netherlands (Table 3; to see the stimulus used in the control condition see Appendix F).

Table 2

Groups and stimuli

		Stimulus		
Figures	Group	Shade	Annotations	Animation
Set 1	a	+	+	+
Set 2	b	+	+	-
Set 3	c	-	+	+
Set 4	d	-	+	-
Set 5	e	+	-	+
Set 6	f	+	-	-
Set 7	g	-	-	+
Set 8	h	-	-	-
Climate unrelated graph	x	n/a	n/a	n/a

Participants from all conditions were required to spend at least a minute and a half on getting acquainted with the presented stimulus. The question was timed in Qualtrics; therefore, participants could not proceed with the study before that time passed.

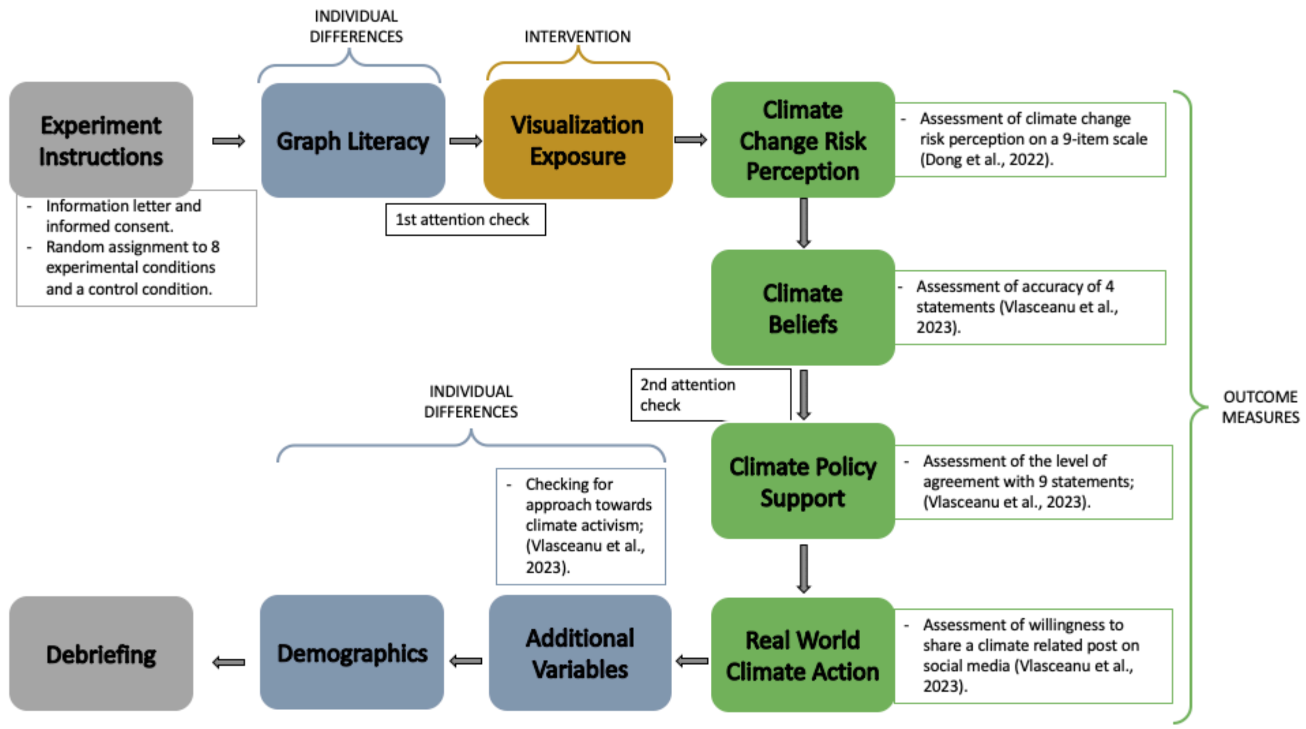
After the exposure to the assigned stimulus, participants were asked to fill in the risk perception scale followed by the climate beliefs questionnaire. After completing those two questionnaires, participants were exposed to the second and the last attention check. In the upcoming sections participants were asked to fill in questionnaires examining climate policy support, real world action and approach towards climate activism, in that order.

When answering the real-world action questionnaire, participants who indicated they are willing to share the post on social media were given a minute to do so. The activity was timed in Qualtrics; therefore, participants were not able to proceed with the study before a minute passed. After a minute, participants were asked whether they actually shared the post and if so, they were asked to indicate the platform where the post was shared. Participants who indicated that they do not use social media were automatically redirected to the last section of the study, being demographics.

Demographics information that we collected consisted of gender, age, and education. In the end, all the participants were debriefed. The entire experiment was estimated to last 20 to 30 minutes. For the full overview of the study procedure see Figure 4.

Figure 4.

Diagram visualising the experimental procedure.



Statistical Analysis

Descriptive Statistics

Descriptive statistics included all experimental groups and the control group. The chosen visualisation method for continuous variables was a boxplot. The goal was to visualise differences in means between all the groups. We used stacked bar charts to visualise differences in participants counts for intention to share and sharing, and graph literacy variables. Intention to share and actual sharing variables were coded into numerical values and we calculated averages using those values. Therefore, all the participants who were willing to and who actually shared the social media post had an average of 1; all the participants who were willing to but who did not the social media post had an average of 0.5; finally, all the participants who were not willing to and who did not share the social media post had an average of 0. We used average scores to investigate participants' performance on graph literacy questionnaire. There were four possible outcomes depending on how many questions were answered correctly; participants could obtain a total score of either 0, .25, .5, .75 or 1.

Additionally, correlations between all the outcome measures and the covariates were checked for. By checking for correlations, we aimed to understand the relationship between the variables in this study.

Inferential Statistics: group "h" vs group "x"

An independent samples T-test was conducted to examine any differences between participants exposed to the basic climate change related graph compared to climate change unrelated graph. By doing so, we wanted to investigate whether the exposure to the simplest climate change related graph may already lead to some differences in our participants' responses, compared to participants who were not exposed to any climate change related content at all. Therefore, two groups included in this analysis were group "x" (the control group) and group "h" (group "h" was exposed to the most basic graph not including any design dimensions, i.e. no shade, no annotations and no animation). Therefore, groups from "a" to "g" were excluded from this analysis. The dependent variables in those analyses were: risk perception, climate beliefs and climate policy support. The assumptions of normality and homogeneity of variance were checked for.

In order to investigate differences in the nominal outcome measure we used contingency tables. We excluded groups from “a” to “g”, as well as participants who indicated they do not use social media. Firstly, intention to share a social media post was used as a dependent variable with two categories: intention to share and no intention to share. Secondly, actual social media post sharing was used as a dependent variable with two categories: shared and did not share.

Inferential Statistics: between experimental groups comparison

Further analyses excluded the initial control group. The aim was to avoid unequal group sizes, as the sample was not split by the “group” variable anymore. Instead, we used “shade”, “annotation” and “animation” as the grouping variables. The goal was to investigate the effects of different design dimensions and their combinations on outcome measures compared to the simplest climate change graph, which did not include any design dimensions. Therefore, the group exposed to a climate change unrelated graph was irrelevant in those analyses and the group “h” became the control group in the following analyses.

Despite the ordinal nature of the scales’ outcomes, they were treated as continuous variables. Research suggests that when using Likert-type the estimates improve if the answer scales have more than three points and a sample size of 300 participants, which is the case in the current study (Hagen et al., 2015; Owuor, 2001).

In order to investigate all three hypotheses (Figure 2), 3 between-subject ANOVAs were conducted on 3 outcome variables: risk perception, climate beliefs and policy support. Shade, Annotations, Animation were used as fixed factors in these analyses. The assumptions of normality and homogeneity of variance were checked for. After each ANOVA, a post hoc analyses of ANCOVA were conducted with graph literacy and climate activism as covariates.

To check how appropriate the chosen covariates were, we looked up the correlations from the Descriptive Statistics section; ideally covariates are not strongly correlated with one another and there is a linear relationship between each covariate and each dependent variable (Pallant, 2010). The assumption of homogeneity of variance was checked for all ANCOVAs and ANOVAs by using the Levene's Test. The assumption of homogeneity of regression slopes was checked for all ANCOVAs. Finally, all the effect sizes were assessed according to guidelines proposed by Cohen (1988, pp. 284 – 7): .01 = small effect, .06 = moderate effect, .14 = large effect.

Due to the nominal nature of the variables: intention to share a social media post and actual social media post sharing variables, we conducted a factorial logistic regression on each of those variables. Participants who indicated they do not use social media were excluded from this analysis. The dependent variable in the first logistic regression was the intention to share a social media post and the dependent variable in the second logistic regression was the actual social media post sharing. Shade, Annotations, Animation were used as fixed factors in these analyses. After each linear regression, a post hoc analysis of linear regression was conducted with graph literacy and approach towards climate activism as covariates. The p-value threshold for statistical significance for all inferential statistics was .005 to improve the reproducibility of this scientific research (Benjamin et al., 2017).

Results

Descriptive statistics

Group sizes were close to equal, despite excluding some of the participants who missed the attention checks. The exceptions were groups for "intention to share" and "actual sharing" variables. The differences in group sizes for "intention to share" were due to participants who indicated they do not use social media and were excluded from the analysis of this variable. The differences in group sizes for "actual sharing" were due to participants who indicated they do not use social media and participants who expressed no intention to share the social media post, and hence, were excluded from the analysis of this variable (Table 3).

Table 3.

Descriptive statistics for outcome measures and covariates

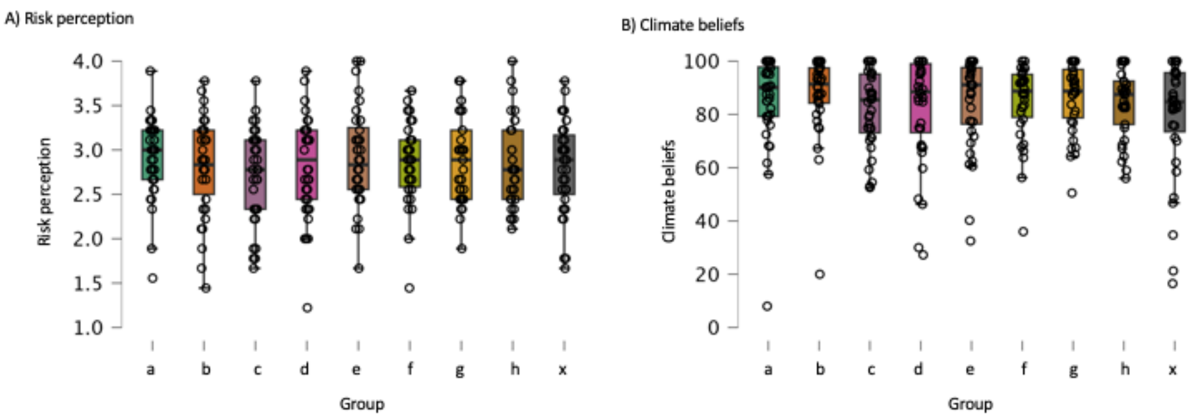
Group		Risk perc.	Climate beliefs	Policy support	Intention to share	Actual sharing	Activism	Graph literacy
a	N	36	36	36	20	5	36	36
	M	2.9	85.5	75.8	.3	.8	63.6	.7
	SD	.5	17.8	12.7	.4	.5	14.5	.2
b	N	34	34	34	23	8	34	34
	M	2.8	87.6	80.6	.4	.3	72.3	.638
	SD	.6	15.4	13.6	.5	.5	10.1	.217
c	N	35	35	35	21	2	35	35
	M	2.7	82.1	76.6	.1	1	64.2	.7
	SD	.5	14.5	15.7	.3	0	13.9	.3
d	N	36	36	36	25	6	36	36
	M	2.8	82.4	77.7	.2	.3	64.2	.7
	SD	0.6	20	17.8	.4	.5	12.5	.2
e	N	36	36	36	28	8	36	36
	M	2.9	84.5	77.8	.3	.4	66.2	.7
	SD	.5	17.3	14.2	.5	.5	11.8	.2
f	N	34	34	34	30	4	34	34
	M	2.9	84.6	77.1	.1	.8	63.8	.7
	SD	.5	14.3	13.9	.4	.5	13.5	.2

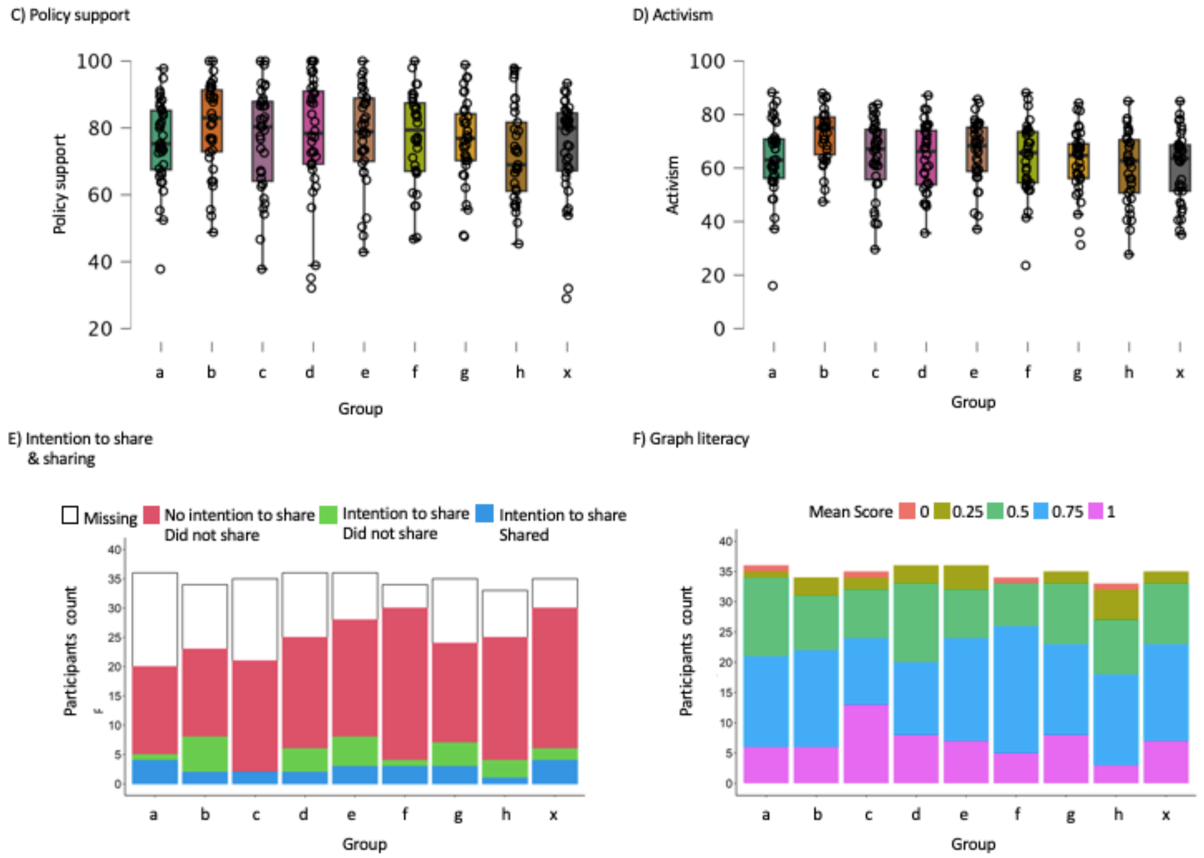
Group		Risk perc.	Climate beliefs	Policy support	Intention to share	Actual sharing	Activism	Graph literacy
g	N	35	35	35	24	7	35	35
	M	2.9	86.5	76.2	.3	.4	62.5	.7
	SD	.5	12.9	12.7	.5	.5	12.5	.2
h	N	33	33	33	25	4	33	33
	M	2.8	84.5	72.1	.5	.3	60.2	.6
	SD	.5	12.9	14.2	.4	.5	13.8	.2
x	N	35	35	35	30	6	35	35
	M	2.8	79.2	74	.2	.7	60.7	.7
	SD	.5	22.3	15.2	.4	.5	13.2	.2

The summary of the data collected for each outcome variable and each covariate is visualised in Figure 5.

Figure 5.

Visual summary of descriptive data for all outcome measures and variables.



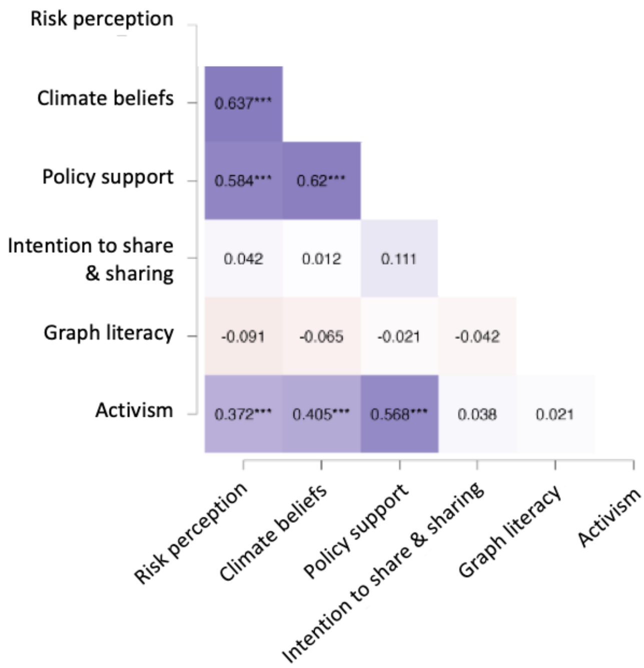


Risk perception, climate beliefs, policy support and climate activism were not normally distributed, as assessed by Shapiro-Wilk's test (risk perception with p = .046, climate beliefs with p < .001, policy support with p < .001, climate activism with p < .001). Values of skewness and kurtosis for risk perception and policy support ranged between -1 and 1, meaning that *F*-test we had planned to conduct on those variables remained robust (Blanca et al., 2017). It was not the case for the climate beliefs variable, however, according to Blanca et al.'s (2017) recommendations, heterogeneity has a greater effect on *F*-test robustness than does non-normality. Therefore, we decided to conduct ANOVA on that variable too, after checking for the significance of the Levene's test. If Levene's test was significant, the next step would have been conducting the Kruskal-Wallis test instead of ANOVA.

We used Spearman's rho correlation coefficient to check for correlations between variables. Risk perception, climate beliefs and policy support were all strongly correlated to one another. Out of the two confounders in the current study, climate activism was correlated with risk perception, climate beliefs and policy support. Graph literacy was not correlated with any of the outcome measures; it was expected as graph literacy is not a continuous variable itself and it comes with four possible outcomes. The same rationale applies to intention to share and sharing variable, which is an average extracted from two binomial outcomes (see Figure 6; for full correlation matrix see Appendix G). In the upcoming paragraphs we proceed with the hypotheses testing.

Figure 6.

Correlations between outcome measures with flagged significant correlations; for full correlation matrix see Appendix G.



* p < .05, ** p < .01, *** p < .001

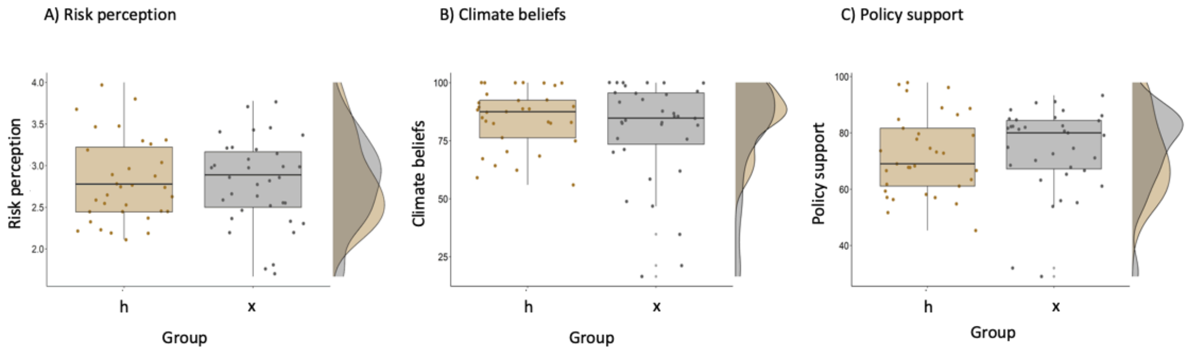
Inferential Statistics: group "h" vs group "x"

To examine differences between participants exposed to the basic climate change related graph compared to climate change unrelated graph, we conducted the independent samples T-test. There were no significant differences between group "h" and group "x" on any of the continuous outcome measures [$t_{risk\ perception}(66) = -.09$, $p = .927$, Cohen's d = -.02, indicating a small effect;

$t_{policy\_support}(66) = .536$, $p = .594$, Cohen's d = .13, indicating a small effect]. The homogeneity assumption of variance was violated for climate beliefs variable [Levene's test: $F(1, 66) = 4.91$, $p = .30$]. Therefore, we reported the alternative value of t-test for climate beliefs that assumes unequal variances [$t_{climate\_beliefs}(66) = -1.20$, $p = .237$, Cohen's d = -.29, indicating a small effect].

Figure 5.

Differences in continuous outcome measures' scores between group "h" and group "x".



The result of the Fisher's exact test did not indicate any difference in the proportion of participants who expressed they are willing to share the social media post and the participants who were not willing to share the social media post depending on which group they were assigned to ($p = .741$). Fisher's exact test also did not indicate any difference in the proportion of participants who shared the social media post and the participants who did not share the social media post depending on which group they were assigned to ($p = .524$).

Inferential Statistics: between experimental groups comparison

For the next step we excluded the group exposed to the climate change unrelated graph and focused on groups exposed to data visualisations designed by us. We aimed to investigate the effects of different design dimensions and their combinations on outcome measures compared to the simplest climate change graph, which did not include any design dimensions. We expected all the groups exposed to any of the dimensions or their combinations to have higher scores on outcome measures compared to the group not exposed to any of the dimensions or their combinations.

None of the dimensions or their interactions had any effect on risk perception, with all p-values ≥ .258. All results of this ANOVA had $\eta_p{}^2 \leq .005$, indicating very small effects. We ran ANCOVA with the same dependent and independent variables to control for our participants' graph literacy and approach towards climate activism. Graph literacy was not a significant covariate [$F(1,269) = 3.85$, $p = .051$, $\eta_p{}^2 = .014$, indicating a small effect], in contrast to the approach towards climate activism [$F(1,269) = 47.90$, $p < .001$, $\eta^2 = .151$, indicating a large effect]; it could be already predicted based on the result of the correlation matrix. The assumption of homogeneity of regression was violated for shade*annotations*activism [$F(1,262) = 4.24$, $p = .040$, $\eta_p{}^2 = .016$, indicating a small size effect]. After controlling for both of the covariates, no effects of design dimensions or their interactions were found, with all p-values ≥ .61 and $\eta_p{}^2 \leq .013$. Given the exploratory nature of graph literacy as a covariate and its small effect, we also ran an ANCOVA with the approach towards climate activism covariate only. We found no significant effects after adjusting for the effect of climate activism, with all p-values ≥ .070 $\eta_p{}^2 \leq .012$. In this ANCOVA, the assumption of homogeneity of regression was violated for shade*annotations*activism [$F(1,263) = 4.51$, $p = .035$, $\eta_p{}^2 = .017$, indicating a small size effect].

Participants' climate beliefs were not affected by any of the three dimensions or their combinations; all with p-values ≥ .171 and $\eta_p{}^2 \leq .007$, indicating very small effects. Same as in previous analysis, graph literacy was not a significant covariate [$F(1,269) = 4.54$, $p = .034$, $\eta_p{}^2 = .017$, indicating a small effect], and climate activism was a significant one [$F(1,269) = 73.95$, $p < .001$, $\eta_p{}^2 = .216$, indicating a large effect]. No significant effects were found when adjusting for both covariates, with all p-values ≥ .179 and $\eta_p{}^2 \leq .007$. The assumption of homogeneity of regression was violated for annotations*activism [$F(1,262) = 4.40$, $p = .037$, $\eta_p{}^2 = .017$, indicating a small effect]. No significant effects were found when adjusting for climate activism only, with all p-values ≥ .130 and $\eta_p{}^2 \leq .008$.

The assumption of homogeneity of regression was violated for annotations*activism [F(1,263) = 5.277, p = .022, $\eta_p{}^2$ = .020, indicating a small effect].

None of the dimensions or their combinations had an effect on policy support, all with p-values ≥ .121 and small effects of $\eta_p{}^2 \leq$ .009 (for visual summary of all three ANOVAs see Appendix H). As in previous ANCOVA analyses, graph literacy was not a significant covariate [F(1,269) = .29, p = .59, $\eta_p{}^2$ < .001] and climate activism was a significant one [F(1,269) = 141.81, p <.001, $\eta_p{}^2$ = .345]. No significant effects were found after adjusting for these covariates, with all p-values ≥ .328 and $\eta_p{}^2 \leq$ .004. No effects were found after controlling for climate activism only, with all p-values ≥ .335 and $\eta_p{}^2 \leq$ .003. The assumption of homogeneity of regression was not violated for either of the ANCOVAs conducted with policy support as the dependent variable.

The results of logistic regression showed no significant relationship between intention to share social media post and the predictor variables [shade, annotations, animation; X^2(192) = .95, p = .813]. Moreover, Nagelkerke R^2 = .007 indicated a poor model fit, as it is suggested that a range from 0.2 to 0.4 indicates a good model fit (Goss-Sampson, 2020). After adding graph literacy and climate activism as covariates, the model remained insignificant [X^2(190) = 1.88, p = .866, Nagelkerke R^2 = .015, indicating a poor model fit].

We run another logistic regression to investigate the relationship between actual sharing of the social media post and the predictor variables (shade, annotations, animation). The analysis showed no significant relationship between the dependent variable and predictors (X^2(40) = 2.05, p = .562, Nagelkerke R^2 = .061, indicating a poor model fit). Adding graph literacy and climate activism as covariates did not improve our model (X^2(38) = 8.44, p = .134, Nagelkerke R^2 = .233).

Discussion

This research aimed to find empirical evidence for the effects of three design guidelines (shade, annotations, animation) applied to carbon emissions scenario figures on: climate change risk perception, climate beliefs, climate policy support and real-world action. We expected all the groups exposed to any of the dimensions or their combinations to have higher scores on outcome measures compared to the group(s) not exposed to those dimensions or their combinations. No effects of shade, annotations or animation were found on any of the outcome variables. No effects of combinations of these design dimensions were found either. There are a few things that should be considered in interpretation of the results of the current research.

Firstly, scores on risk perception, climate beliefs and climate policy support were highly skewed across groups; scores across all groups on those three aforementioned outcome variables were above average, and often reached ceiling. Our sample consisted mostly of bachelor students and people with other higher education degrees (Henrich et al., 2010). Higher education increases the exposure to climate science and to the norms of one's political ingroup, which can explain biased samples in this study despite random assignment to experimental groups (Ballew et al., 2020; Ehret et al., 2016; Bohr, 2014). Overall, a bigger and more heterogeneous sample is recommended for future research. Running Bayesian ANOVA is recommended to establish whether our results actually indicated no effect, or it was a matter of too low power of conducted tests.

Another interesting aspect that should be investigated in future studies is the nationality of participants. We did not gather this type of data, however, considering how many international students study at Leiden University, one could assume that our sample included students with nationalities other than Dutch. Public perceptions of climate change vary among geographical regions and can change over time (Hagen et al., 2015; Department of Transport, 2010). Hagen et al. (2015) conducted a study that focused on public perceptions of climate change and relevant mitigation and adaptation policies in Spain, Netherlands, UK and Germany. The results of this study indicated differences between those four countries and therefore, it would be interesting to implement that knowledge and control for the effect of place of one’s origin on climate change perception. Nationality could be a better covariate in our study, especially that we aimed to measure climate beliefs and climate policy support post climate data visualisation exposure. In the study of Vlasceanu et al., (2023), the country of origin was also used as the random effect in their analysis. For instance, willingness to share climate–change related information on social media varied among countries, ranging from a low of 17.6% in Latvia to a high of 93.3% in Kenya, showing that climate-change discussion online may reflect different local norms rather than global views about the reality of climate change (Vlasceanu et al., 2023). Therefore, controlling for this cofounder may be essential in order to avoid bias in end results.

After reflecting on how big of a role one's environment plays in climate beliefs and climate policy support, we also acknowledged that a single short viewing of data visualisation may not be immersive enough to change those beliefs and policy support. Data visualisation is a great tool for conveying facts, however, definitely more than this is needed to drive a societal change. It would be interesting to investigate whether duration and frequency of exposure to our climate scenario figures has an effect on the dependent variables chosen for the current study, as well as the context and medium in which they are presented, such as for example a newspaper, lecture or talk with business owners.

A technical aspect of measuring our dependent variables and one of the covariates that could be improved is the placement of the sliders in questionnaire. All of the sliders in our questionnaires were anchored at 0 or 1 (see Appendices A, B, C, E). Intermixing positioning of sliders should be considered in the future, in order to avoid biasing the respondents of the survey (Gehlbach & Barge, 2012).

Investigating and finding relevant confounders and covariates is a very important suggestion for future research, as covariates in the current study did not seem to be well chosen. Graph literacy was not a significant predictor in any of the ANACOVAs we conducted. Climate activism, on the other hand, interacted with risk perception and climate beliefs variables. This means that relationships between climate activism and those outcome measures may not have been the same across all the groups. It raised some concerns regarding the validity of those ANCOVAs analyses. Hence, better predictors, such as nationality which is connected to climate change public perceptions, should be considered in future research.

Moreover, covariates were collected together with all the dependent variables, in other words, while the study was conducted on our participants. A better solution would be assessing covariates before the experiment took place. During our study we also collected other demographic data such as sex, age and education. Investigating these variables in depth was beyond the scope of this master thesis project, and we suggest that future studies could benefit from doing so.

Considering that a lot of participants had to be excluded from analyses, in which intention to share and actual sharing of the social media post were dependent variables, there was a problem with conducting logistic regressions. It could be a partial explanation for poor model fit in both analyses. Therefore, social media post sharing was not an effective measure of the real-world action in the current study. Most participants indicated they do not use social media or are simply not willing to share the social media post. This could be explained by the spiral of silence theory. The theory explains that people avoid using social media to express their opinions in order to avert social sanctions (Bäck et al., 2018). The study of Bäck et al (2018) interviewed 60 Swedish students and showed that this tendency can be even stronger in young people, who refrain from making claims that are not accepted by their peers.

Hence, it makes sense that most of our participants did not decide to share the social media post on their social media accounts. Except for our sample consisting of young students, there is also a strong political divide on climate change. The study of McCright et al. (2015) showed that citizens on the left consistently reported stronger belief in climate change and support for action to mitigate it than did citizens on the right in 14 Western European countries. Given the uncertainty about sharing political views in social media, and how easily social acceptance, or rejection, can be communicated through, for instance, likes, it may be that our participants were less likely to share climate change related information on their social media for that reason (Bäck et al., 2018).

Given those findings, we suggest a different measure of climate real world action: Work for Environmental Protection Task (WEPT; Lange & Dewitte, 2022). On WEPT participants can choose to make real voluntary efforts by screening stimuli for specific numerical combinations (i.e., an even first digit and odd second digit), to produce actual donations to an environmental organisation (Lange & Dewitte, 2022; Vlasceanu et al., 2023). Therefore, it does not involve communicating participants' stance on climate change action to a broader audience in any way. The reason why we did not use that measure were both the financial and time restrictions of this master thesis project.

We are aware of the methodological limitations of this study and their implications. However, the lack of any differences between the groups also tells us something about the previous research and its generalizability. We did not find any between groups differences, even when comparing only the group exposed to a climate change unrelated graph with the group, which was exposed to the different carbon scenario figures with no design dimensions applied. We have worked with evidence-based recommendations on how to improve data visualisations, however, they did not have an effect on any of the outcome measures. One of the reasons for no significant results may be the vagueness concerning how and to what type of visualisations some of the design guidelines should be applied to be effective. Kale, Kay and Hullman (2021) investigated different uncertainty visualisation designs and concluded that the theory of how to design one's visualisations may not be always effective. It is because users use different heuristics, as well as different, often not the most optimal, strategies for understanding presented visualisations (Kale et al., 2021). It may also partially explain results of the current study, which did not control for the heuristics the end-users of our visualisations were using to understand the message we were trying to convey.

For that reason, some suggest using the user-centred design (UCD) framework, in which user characteristics (needs, wants and limitations) are given explicit consideration throughout the whole design process (Grainger et al., 2016; Beyer & Holtzblatt, 1998). It facilitates creating user-tailored visualisations. However, such a procedure seems to be very time- and cost-consuming, if we consider applying it every time there is a need for data visualisation. Therefore, it is more of a well thought-through choice based on a lot of factors, such as time and costs available for a project, rather than a general and easily applicable recommendation for facilitating mass communication by NGOs and governments. Future research could investigate alternative ways of applying this framework or come up with a more accessible alternative to it.

The focus on the user is very important, however, we also think that designers should be given sufficient attention too. In the end, same as the end-users, they also use different heuristics and strategies for creating and understanding their own visualisations. How can we make sure that design guidelines taken from the literature are applied in the same or at least a similar way? In the review of Terrado et al., (2022), they describe the most commonly applied practices for visualisations; for instance, they say that pre-attentive elements, such as colour or motion, can facilitate information processing of users (Terrado et al., 2022; Janes et al. 2013). In the current study we used shade as a pre-attentive element. which did not seem to make our visualisations more impactful in any way. Did we use the wrong pre-attentive element? Or did we apply it in the wrong way? This is the example of how vague literature recommendations are, making them less comprehensive and just difficult to apply in the “right” way by everyone. Hence, we suggest that future studies should focus more on precising the already existing guidelines and design principles.

Another aspect that should be investigated in order to improve (climate) data visualisations is a transdisciplinary approach. According to various studies, transdisciplinary aspects have received little attention in the climate services field (Terrado et al., 2022; McInerny et al. 2014; Estrada & Davis 2014). Already when we were designing graphs for the current study, the input of the climate change activist, Hiske Arts, had a huge impact on how we, cognitive psychologists, moved forward with the project. Stepping outside our disciplinary boundaries by consulting experts from other fields, such as for example the visual arts and computer science, could possibly allow us to come up with solutions that would have otherwise been unreachable (Grainger et al., 2016; McInerny et al., 2014; Vervoort et al., 2014, Kosara, 2013a).

Conclusion

In this research we applied a few visualisation guidelines on carbon emissions scenario figures. By doing so, we wanted to help the viewers of those visualisations understand the cumulative effect of CO_2 emissions and thus, why taking climate action is necessary right now. We aimed to find empirical proof for the effects of adding shade, annotations and guided animation on climate change risk perception, climate beliefs and policy support, and climate action. Our results did not show any effects of application of the chosen design dimensions. This may be partially a result of the current study's limitations, such as homogenous and small sample and the validity of chosen measures. Therefore, we came up with specific suggestions for the future research that aim to target and eliminate those methodological limitations. However, it is also important to acknowledge and address the gaps of knowledge we came across while looking for explanations to reach beyond the statistical results of our study. It is definitely very difficult, if not impossible, to create universal design guidelines which would become a “one-size-fits-all” approach. Nevertheless, it is possible to make those guidelines more specific in terms of their application. Moreover, combining user-centred and transdisciplinary approaches could benefit the (climate) data visualisations hugely, especially when targeting the non-expert audiences. Taking all those aspects into account, future research could really take a great step towards improving data visualisation as a communication tool between experts and non-experts. It is really important for this and other communication tools to bridge gaps between people. As a result, we should be able to take collective action with everyone being fully aware of the urgency of doing so to save our planet.

References

Bäck, E., Bäck, H., Fredén, A., & Gustafsson, N. (2018). A social safety net? Rejection sensitivity and political opinion sharing among young people in social media. *New Media & Society*, *21*(2), 298–316. https://doi.org/10.1177/1461444818795487

Ballew, M. T., Pearson, A. R., Goldberg, M. H., Rosenthal, S. A., & Leiserowitz, A. (2020). Does socioeconomic status moderate the political divide on climate change? The roles of education, income, and individualism. *Global Environmental Change*, *60*, 102024. https://doi.org/10.1016/j.gloenvcha.2019.102024

Beyer, H., & Holtzblatt, K. (1999). Contextual design. *interactions, 6*(1), 32-42.

Benjamin, D. J., Berger, J. O., Johannesson, M., Nosek, B. A., Wagenmakers, E. J., Berk, R. A., Bollen, K. A., Brembs, B., Brown, L. D., Camerer, C. F., Cesarini, D., Chambers, C. D., Clyde, M. A., Cook, T. D., De Boeck, P., Dienes, Z., Dreber, A., Easwaran, K., Efferson, C., . . . Johnson, V. E. (2017). Redefine statistical significance. *Nature Human Behaviour, 2*(1), 6–10. https://doi.org/10.1038/s41562-017-0189-z

Blanca, M. J., Alarcón, R., Arnau, J., Bono, R., & Bendayan, R. (2017). Non-normal data: Is ANOVA still a valid option? *PubMed, 29*(4), 552–557. https://doi.org/10.7334/psicothema2016.383

Buis, A. (2019, October 9*). The Atmosphere: Getting a Handle on Carbon Dioxide Sizing Up Humanity's Impacts on Earth's Changing Atmosphere: A Five-Part Series.* NASA's Jet Propulsion Laboratory. https://climate.nasa.gov/news/2915/the-atmosphere-getting-a-handle-on-carbon-dioxide/

Bohr, J. (2014). Public views on the dangers and importance of climate change: predicting climate change beliefs in the United States through income moderated by party identification. *Climatic Change, 126*(1–2), 217–227. https://doi.org/10.1007/s10584-014-1198-9

Carrington, D. (2021, August 25). Christiana Figueres on the climate emergency: 'This is the decade and we are the generation.' The Guardian.

https://www.theguardian.com/environment/2020/feb/15/christiana-figueres-climate-emergency-this-is-the-decade-the-future-we-choose

Cohen, J.W. (1988). Statistical power analysis for the behavioral sciences (2nd edn). Hills-dale, NJ: Lawrence Erlbaum Associates.

De Jong, T. (2009). Cognitive load theory, educational research, and instructional design: some food for thought. *Instructional Science, 38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0

Department of Transport. 2010. *Public Attitudes Towards Climate Change and the Impact of Transport: 2006, 2007, 2008, and 2009*. GOV.UK: London.

Dong, X., Geng, L., & Casallas, J. D. R. (2022). How is cognitive reappraisal related to adolescents' willingness to act on mitigating climate change? The mediating role of climate change risk perception and believed usefulness of actions. *Environmental Education Research*, 1–22. https://doi.org/10.1080/13504622.2022.2120188

Estrada, F. C. R., & Davis, L. S. (2014). Improving visual communication of science through the incorporation of graphic design theories and practices into science communication*. Science Communication, 37*(1), 140–148. https://doi.org/10.1177/1075547014562914

Ehret, P. J., Sparks, A. C., & Sherman, D. K. (2016). Support for environmental protection: an integration of ideological-consistency and information-deficit models. *Environmental Politics, 26*(2), 253–277. https://doi.org/10.1080/09644016.2016.1256960

Franconeri, S., Padilla, L., Shah, P., Zacks, J. M., & Hullman, J. (2021). The Science of Visual Data Communication: What Works. *Psychological Science in the Public Interest, 22*(3), 110–161. https://doi.org/10.1177/15291006211051956

Gehlbach, H., & Barge, S. (2012). Anchoring and adjusting in questionnaire responses. *Basic and Applied Social Psychology, 34*(5), 417–433. https://doi.org/10.1080/01973533.2012.711691

Goss-Sampson, M.A. (2020). *Statistical analysis in JASP: a guide for students*. JASP. https://doi.org/10.6084/m9.figshare.9980744

Grainger, S., Mao, F., & Buytaert, W. (2016). Environmental data visualisation for non-scientific contexts: Literature review and design framework. *Environmental Modelling and Software, 85*, 299–318. https://doi.org/10.1016/j.envsoft.2016.09.004

Hagen, B., Middel, A., & Pijawka, D. (2015). European Climate Change Perceptions: Public support for mitigation and adaptation policies. *Environmental Policy and Governance*, *26*(3), 170–183. https://doi.org/10.1002/eet.1701

Harold, J., Lorenzoni, I., Shipley, T. F., & Coventry, K. R. (2016). Cognitive and psychological science insights to improve climate change data visualization. *Nature Climate Change, 6*(12), 1080–1089. https://doi.org/10.1038/nclimate3162

Hegarty, M. (2011). The Cognitive Science of Visual-Spatial Displays: Implications for Design. *Topics in Cognitive Science, 3*(3), 446–474. https://doi.org/10.1111/j.1756-8765.2011.01150.x

Henrich, J., Heine, S., & Norenzayan, A. (2010). The weirdest people in the world*? Behavioral and Brain Sciences, 33*(2–3), 61–83. https://doi.org/10.1017/s0140525x0999152x

IPCC, 2022: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. *Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA*, 3056 pp., https://doi.org/10.1017/9781009325844

Janes, A., Sillitti, A., & Succi, G. (2013). Effective dashboard design. *Cutter IT Journal, 26*(1), 17-24.

Kale, A., Kay, M., & Hullman, J. (2021). Visual Reasoning Strategies for effect size judgments and decisions. *IEEE Transactions on Visualization and Computer Graphics*, *27*(2), 272–282. https://doi.org/10.1109/tvcg.2020.3030335

Kosara, R. (2013a). InfoVis Is So Much More: A Comment on Gelman and Unwin and an Invitation to Consider the Opportunities. *Journal of Computational and Graphical Statistics, 22*(1), 29–32.

https://doi.org/10.1080/10618600.2012.755465

Kruk & Urai (2023). Climate_dataviz. GitHub. https://github.com/anne-urai/climate_dataviz

Kruk & Urai (2023). Net-zero scenarios. Zenodo, https://doi.org/10.5281/zenodo.7767084

Lange, F., & Dewitte, S. (2021). The Work for Environmental Protection Task: A consequential web-based procedure for studying pro-environmental behavior. *Behavior Research Methods, 54*(1), 133–145. https://doi.org/10.3758/s13428- 021-01617-2

Lange, F., & Dewitte, S. (2023). Validity and scope sensitivity of the Work for Environmental Protection Task. *Journal of Environmental Psychology*, *86*, 101967. https://doi.org/10.1016/j.jenvp.2023.101967

Lee-Robbins, E., & Adar, E. (2022). Affective learning objectives for communicative visualizations. *IEEE Transactions on Visualization and Computer Graphics, 29*(1), 1-11.

Li, S., Lindenberger, U., & Bäckman, L. (2010). Dopaminergic modulation of cognition across the life span. *Neuroscience & Biobehavioral Reviews, 34*(5), 625–630. https://doi.org/10.1016/j.neubiorev.2010.02.003

Lowe, R. (2003). Animation and learning: selective processing of information in dynamic graphics. *Learning and Instruction, 13*(2), 157–176. https://doi.org/10.1016/s0959-4752(02)00018-x

Lowe, R. (1999). Extracting information from an animation during complex visual learning. *European Journal of Psychology of Education, 14*(2), 225–244. https://doi.org/10.1007/bf03172967

Marcott, S. A., Shakun, J. D., Clark, P. U., & Mix, A. C. (2013). A Reconstruction of Regional and Global Temperature for the Past 11,300 Years. *Science, 339*(6124), 1198–1201. https://doi.org/10.1126/science.1228026

Mayer, R. E., Hegarty, M., Mayer, S., & Campbell, J. (2005). When static media promote active learning: annotated illustrations versus narrated animations in multimedia instruction. *Journal of Experimental Psychology: Applied, 11*(4), 256–265. https://doi.org/10.1037/1076-898x.11.4.256

McCright, A. M., Dunlap, R. E., & Marquart-Pyatt, S. T. (2015). Political ideology and views about climate change in the European Union. *Environmental Politics*, *25*(2), 338–358. https://doi.org/10.1080/09644016.2015.1090371

McInerny, G. J, Chen, M., Freeman, R., Gavaghan, D., Meyer, M., Rowland, F., Spiegelhalter, D.J., Stefaner, M., Tessarolo, G., Hortal, J. (2014) Information visualisation for science and policy: engaging users and avoiding bias. *Trends in Ecology and Evolution, 29*(3):148–157. https://doi.org/10.1016/j.tree.2014.01.003

McMahon, R., Stauffacher, M., & Knutti, R. (2015). The unseen uncertainties in climate change: reviewing comprehension of an IPCC scenario graph. *Climatic Change, 133*(2), 141–154. https://doi.org/10.1007/s10584-015-1473-4

Net Zero is a race, not a destination. (2022, November 13). Archy De Berker. https://archy.deberker.com/net-zero-its-the-journey-not-the-destination/

Okan, Y., Janssen, E., Galesic, M., & Waters, E. A. (2019). Using the Short Graph Literacy Scale to Predict Precursors of Health Behavior Change. *Medical Decision Making, 39*(3), 183–195. https://doi.org/10.1177/0272989x19829728

Owuor, C. O. 2001. *Implications of using Likert data in multiple regression analysis.* (Doctoral dissertation, University of British Columbia). https://doi.org/10.14288/1.0053856

Padilla, L., Hosseinpour, H., R, F., Howell, J. L., Chunara, R., & Bertini, E. (2022). Impact of COVID-19 forecast visualizations on pandemic risk perceptions. *Scientific Reports, 12*(1). https://doi.org/10.1038/s41598-022-05353-1

Pallant, J. (2010). SPSS Survival Manual: A step by step guide to data analysis using SPSS. Open University Press.

Pidgeon N, Fischhoff B. 2011. The role of social and decision sciences in communicating uncertain climate risks. Nature Climate Change 1(1): 35–41. https://doi.org/10.1038/NCCLIMATE1080

Shaftel, H. (n.d.). Overview: Weather, Global Warming and Climate Change. Climate Change: Vital Signs of the Planet. https://climate.nasa.gov/global- warming-vs-climate-change/

Stofer, K. A., & Che, X. (2014). Comparing Experts and Novices on Scaffolded Data Visualizations using Eye-tracking. *Journal of Eye Movement Research, 7*(5). https://doi.org/10.16910/jemr.7.5.2

Tversky, B., Morrison, J. B., & Bétrancourt, M. (2002). Animation: can it facilitate? *International Journal of Human-Computer Studies, 57*(4), 247–262. https://doi.org/10.1006/ijhc.2002.1017

Vervoort, J.M., Keuskamp, D.H., Kok, K., Lammeren, R., Van Stolk, T., Veldkamp, T.A., Dezfouli, E.A., Cunningham, K., Nordeman, B., Rowlands, H., (2014). A sense of change: media designers and artists communicating about complexity in social-ecological systems. *Ecology and Society, 19*(3) http://dx.doi.org/10.5751/ES-06613190310.

Vlasceanu, M., Doell, K. C., Bak-Coleman, J. B., & Van Bavel, J. J. (2023, November 20). Addressing Climate Change with Behavioral Science: A Global Intervention Tournament in 63 Countries. https://doi.org/10.31234/osf.io/cr5at

Wang, C., Geng, L., & Rodríguez-Casallas, J. D. (2021). How and when higher climate change risk perception promotes less climate change inaction. *Journal of Cleaner Production, 321*, 128952. https://doi.org/10.1016/j.jclepro.2021.128952

Appendix A

Risk perception scale

Assess using the scale: **1=not at all, 4=very concerned**

1 2 3 4

How concerned are you about global warming?

How likely do you think it is that each of the following will occur during the next 50 years due to global warming? **(1=very unlikely, 4=very likely)**

1 2 3 4

Worldwide, many people's standard of living will decrease.

Worldwide water shortages will occur.

Increased rates of serious disease worldwide.

My standard of living will decrease.

Water shortages will occur where I live.

My chance of getting a serious disease will increase.

Assess using the scale: **1=not at all, 4=very serious**

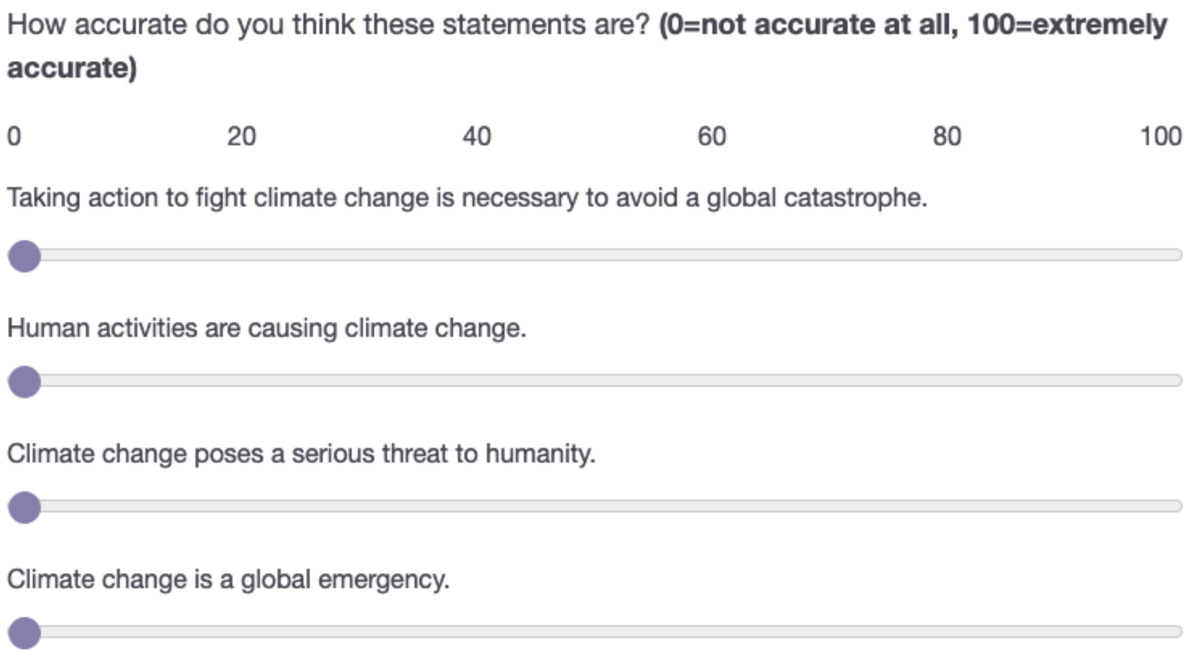
1 2 3 4

How serious of a threat do you believe global warming is to non-human nature?

How serious are the current impacts of global warming around the world?

Appendix B

Climate beliefs scale



How accurate do you think these statements are? **(0=not accurate at all, 100=extremely accurate)**

0 20 40 60 80 100

Taking action to fight climate change is necessary to avoid a global catastrophe.

Human activities are causing climate change.

Climate change poses a serious threat to humanity.

Climate change is a global emergency.

Appendix C

Political support scale

Assess following statements. **(1=not at all, 100=very much so)**

0 20 40 60 80 100

I support raising carbon taxes on gas/fossil fuels/coal.

I support significantly expanding infrastructure for public transportation.

I support increasing the number of charging stations for electric vehicles.

I support increasing the use of sustainable energy such as wind and solar energy.

I support increasing taxes on airline companies to offset carbon emissions.

I support protecting forested and land areas.

I support investing more in green jobs and businesses.

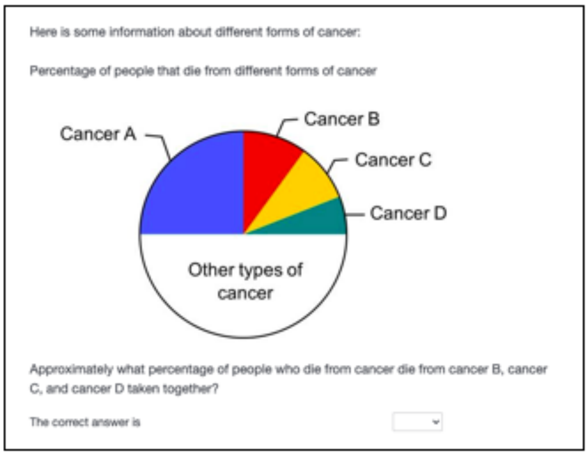
I support introducing laws to keep waterways and oceans clean.

I support increasing taxes on carbon intense foods (for example meat and dairy).

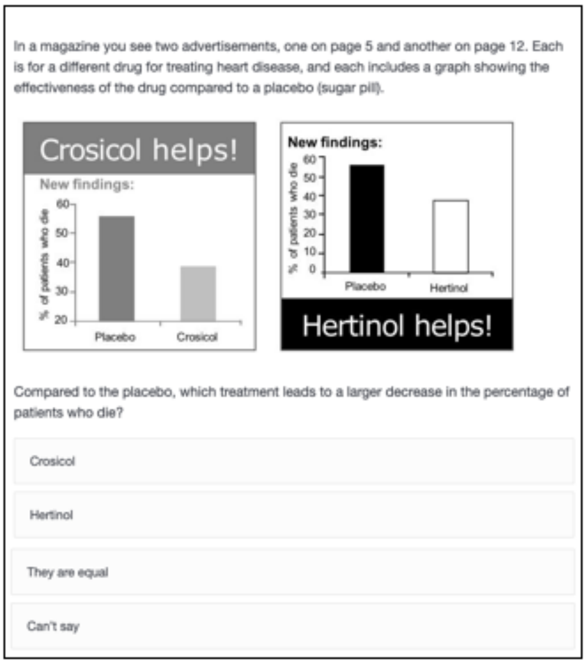
Appendix D

Graph literacy measure

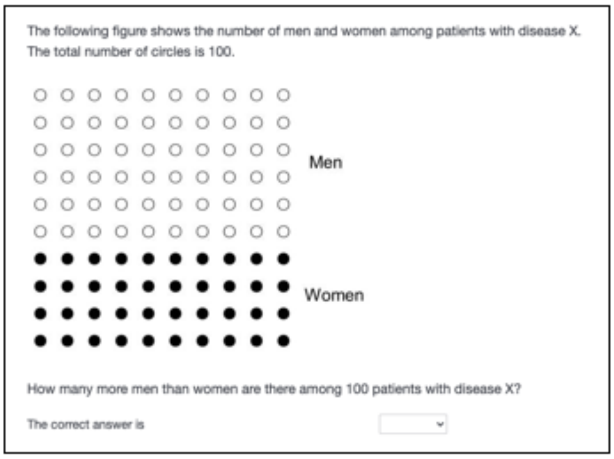
Question 1 (Correct answer: 25%. 24% and 26% accepted)



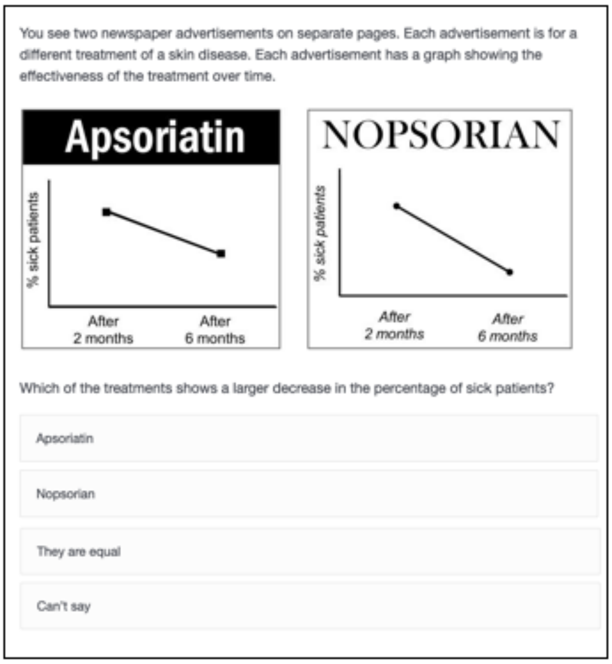
Question 2 (Correct answer: they are equal)



Question 3 (Correct answer: 20)



Question 4 (Correct answer: can't say)



Appendix E

Additional variable (climate activism)

Assess using the scale: **1=not at all, 100=very much so**

0 20 40 60 80 100

On average, how competent are climate change research scientists?

On average, how much do you trust scientific research about climate change?

On average, how much do you trust your government?

To what degree do you see yourself as someone who cares about human welfare

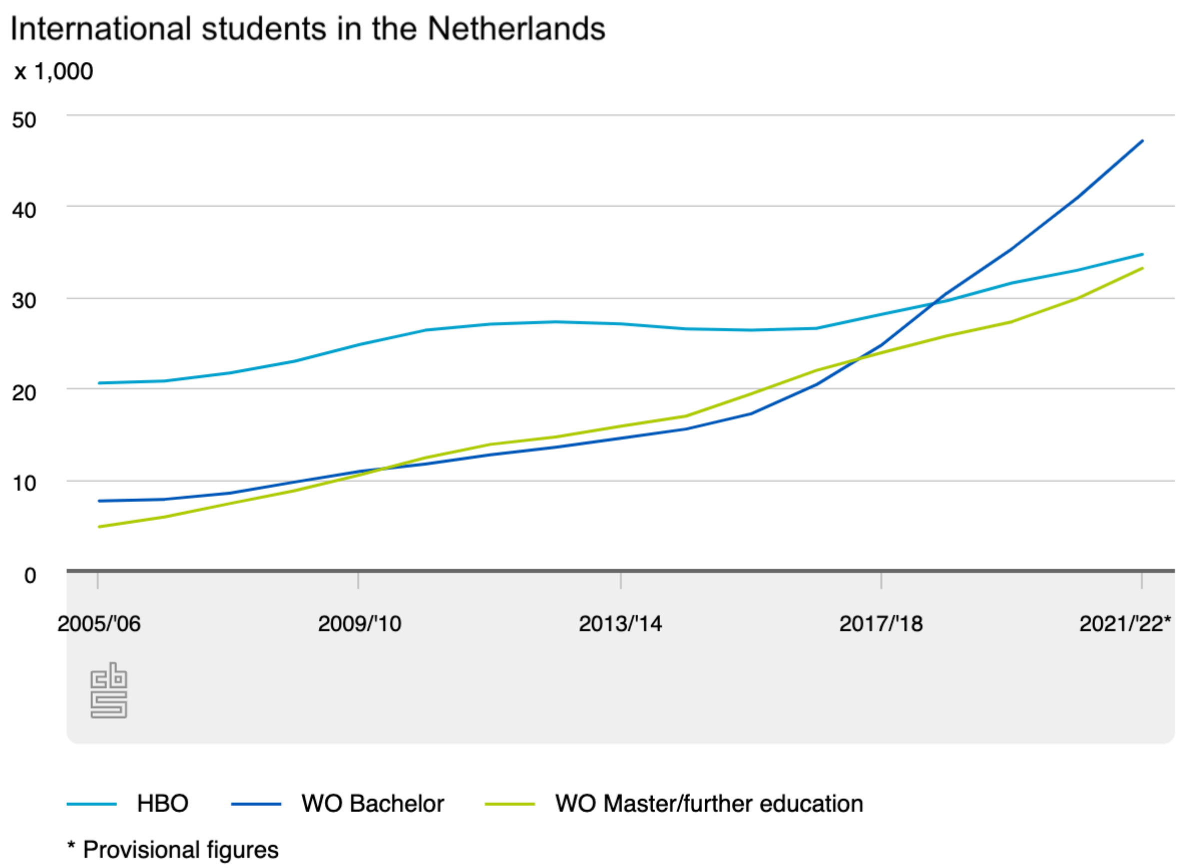
To what degree do you see yourself as a global citizen?

To what degree do you see yourself as someone who cares about the natural environment?

Because of today's politically correct standards, I try to appear pro-environmental.

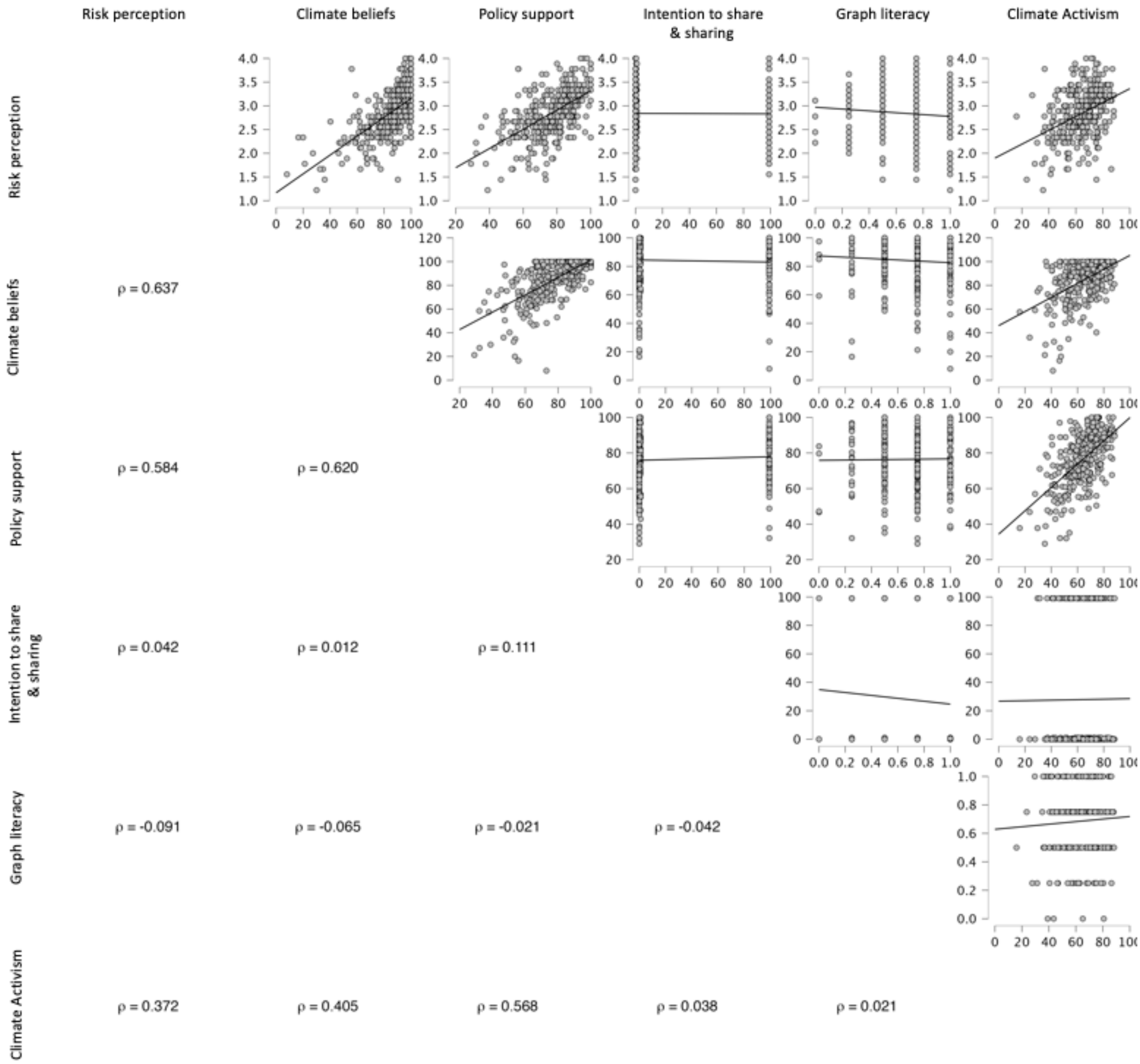
Appendix F

Climate change unrelated graph used for group "x"



Appendix G

Correlation plots for all outcome variables and covariates



Appendix H

Visualisation of ANOVAs’ outcomes