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Effectiveness and Accessibility of Graphical Representations for depicting the COVID-19 Pandemic Hazard

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Abstract

For over two years, Covid-19 maps and visual representations have been used to convey risk information to the public, playing an important role in risk communication and infectious disease prevention. These visual representations often rely on the use of colour to encode risk levels, which may hamper viewers' ability to understand the displayed information in case these have colour vision deficiencies. To study these effects, a web-based survey (n = 161) was conducted to investigate the effect that green-red and blue-gradient colour schemes have on accuracy of interpretation, risk perception and satisfaction of viewers with and without colour blindness. The colour schemes were tested in two different graphical visualizations: a choropleth map and a risk matrix. No clear advantage was found between using green-red or blue-gradient colour schemes in terms of accuracy of interpretation and satisfaction for neither group. In terms of risk perception, green-red colour schemes were shown to decrease the odds of colour-blind individuals rating their intention to adhere to Covid-19 health related guidelines in higher categories in about 61% when compared to full colour vision participants (β = 0.39 (95% CI [0.16;0.968])).

Further studies and testing of colour-blind users' understanding of common colour palettes used for conveying risk information are recommended, to improve the clarity of the effects caused by green-red colour coding in this group of people. This study highlights the importance of studying the efficiency and accessibility of risk visualization for health-related hazards.

Keywords: Information Visualization, Risk Communication, Colour-blindness, Colour Coding, Covid-19.

Resumo

Há mais de dois anos que mapas e representações visuais da evolução da pandemia Covid-19 são utilizados para transmitir informação de risco ao público, desempenhando um papel importante na comunicação de risco e na prevenção da transmissão desta doença infeciosa. Estas representações visuais contam frequentemente com a utilização de cores para codificar níveis de risco, o que pode dificultar a capacidade de compreensão de indivíduos daltónicos, que apresentam anomalias na forma como percecionam as cores. Para estudar estes efeitos, foi realizado um inquérito online (n = 161) para investigar o impacto que os esquemas de cores verde-vermelho e azul-gradiente têm na compreensão, perceção de risco e satisfação dos indivíduos com e sem daltonismo. Os esquemas de cor foram testados em duas visualizações gráficas diferentes: um mapa de coroplético e uma matriz de risco. Não foi encontrada nenhuma vantagem clara entre a utilização de esquemas de cores verde-vermelhos ou azuis-gradiente em termos de compreensão e satisfação para nenhum dos grupos. Em termos de perceção de risco, o esquema de cores verde-vermelho levou a que as chances de indivíduos daltónicos classificarem as suas intenções de aderir a diretrizes de saúde relacionadas com a pandemia Covid-19 em categorias superiores diminuíssem em cerca de 61% quando comparados com indivíduos sem esta condição visual ($\beta = 0.39$ (95% IC [0.16;0.968])).

É recomendada a realização de mais estudos e de testes de compreensão de paletas de cores frequentemente utilizadas para transmitir informação de risco em indivíduos daltónicos, para melhorar a clareza dos efeitos causados pelo uso de cores como verde e vermelho neste grupo de pessoas. Este estudo salienta a importância de estudar a eficiência e acessibilidade de formas de visualização de risco relacionadas com saúde.

Palavras-chave: Visualização de Informação, Comunicação de Risco, Daltonismo, Codificação por Cores, Covid-19.

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1. Introduction, Motivation and Problem

1.1 Introduction

The present work aims to answer the following question: are the Visualizations designed for depicting the Covid-19 Pandemic inclusive, accessible and effective for those that have decreased ability to perceive colour, also known as colour-blind? Several steps are needed to address this question; therefore this piece is divided into different sections, including a literature review on relevant research about this topic and an experiment where a survey was implemented to test two different colour-schemes for displaying risk information in participants with and without colour vision impairments.

Covid-19 risk communication strategy has relied heavily on graphical representations of data to display the pandemic's evolution. Thus, this piece will start by addressing the concept of Information Visualization (shortened as *InfoViz*). It then proceeds to assess what the literature has pointed as the best practices for InfoViz over the years, especially with respect to the use of colour, an element that is recurrently used for portraying Covid-19 information. A section is dedicated to Colour Theory, to address some well-known attributes that help addressing colour – a subjective impression – in an objective manner. After reviewing best practices for colour use, this piece shifts towards the affective side of colour, a critical aspect when studying the impact of using coloured visualizations to perform risk communication.

After this assessment of the important role that colour plays in InfoViz and particularly in Risk Communication, it is time to question whether this element of visualization is accessible and inclusive to all people, focusing on the colour-blind. The human eye, the different types of colour blindness and their impact in visualizing information have a dedicated section, that is followed by what some authors have already gathered as guidelines for colour-design for the vision-impaired.

Lastly, an experiment conducted to assess whether there are better forms of communicating Covid-19 related information is presented, and its results are thoroughly analysed. The experiment consisted of comparing two different colour palettes using two types of data visualizations in groups of people with and without colour vision deficiencies. The responses were gathered using web-based surveys and Prolific[1] platform was used to recruit participants. Rstudio (R Core Team (2020); RStudio Team (2022)) was used to perform all of the result analysis, as well as to create an alternative colour scheme.

[1] https://www.prolific.co/

1.2 Motivation

Since 2020, a phenomenon has grabbed the world's attention for months in a row. The Covid-19 Pandemic ruled the public discussion, to a point where it became usual to have the same headline opening the news everyday: the daily cases of Covid-19, as well as the corresponding mortality rates.

Governmental agencies, media outlets and several other organizations quickly had to find the most effective way for transmitting information to a broad, heterogeneous audience. They were quick to realize that resorting to graphs, maps and other forms of InfoViz was a promising approach to represent this kind of information.

Nevertheless, and in no way disregarding the benefits that Information Visualization brings to the table when it comes to augmenting cognition, one should be careful when using these means of communication. Assuring that the displayed information is understandable, intuitive and, most of all, accessible to everyone is an important matter in all fields of communication, but it sure is crucial in risk communication. Because the Pandemic has developed in what can only be described as an unexpected, unpredictable and fast-paced rhythm, some matters of high importance have not received the necessary attention. This piece seeks to fill in one of those gaps, namely the necessity to account for the needs of vision-impaired people when depicting Covid-19 related information.

The aim of this work is therefore to analyse how inclusive are these visual representations of data for depicting the risk associated to Covid-19 Pandemic, focusing on people with colour vision impairments and whether there are better ways of communicating this information, namely by resorting to alternative colour schemes.

Colour blindness affects approximately 8% of the male population and 0.4% of the female (Keene, 2015). As colour is, in some cases, the most important element to gain insight regarding hazard situations, designers of maps and information graphics should not neglect the needs of this relatively large group of people. Graphic designers should ensure that their work is clear not only to the viewer with full colour vision but to the colour impaired as well. It is a matter of reaching broader audiences with data visualization.

1.3 Problem

The most commonly used colour palettes for conveying risk information rely on the use of red-green colour scales to depict different levels of hazard (Brewer, 2006) (Engeset et al., 2022). This happens as graphic designers often opt for intuitive colour coding, meaning that they choose colours that are frequently paired together to display particular concepts or messages, as these pairings create strong, implicit colour associations, such that the mere perception of these colours evokes a given interpretation (Elliot & Maier, 2014). Using red and green together is one of such pairings, as in western societies green is associated with safeness and red with danger (Bartels & van Beurden, 1998).

Red-green colour maps, although remaining prevalent in science, are difficult to read to those with colour-vision deficiency (Crameri et al., 2020) (Brewer, 2006), especially when they contain similar luminosities, which makes maps and other types of graphical representations hard or even impossible to interpret by citizens with colour vision deficiencies (Crameri, 2018). Effective risk design should take a minimum amount of time to be accurately interpreted, universally understood and efficient. Strictly following colour codes that have become ordinary for showcasing risk information may lead to the oversight of the needs of those with colour vision deficiencies. By simulating how some of these representations are perceived by colour-blind users, one can become aware of how challenging it can be to interpret these, as can be seen in Figure 1 and in Figure 2 (whose terms are defined on Section 2.5).

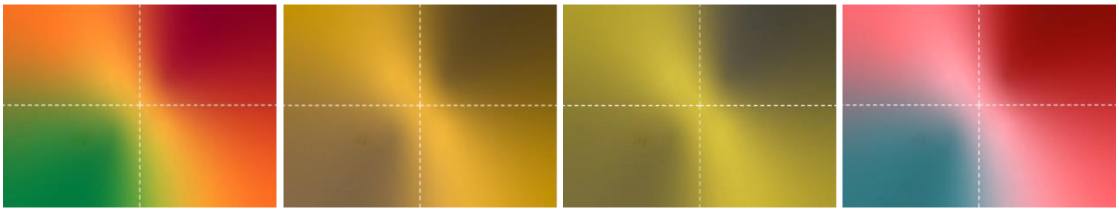

Figure 1 – Covid-19 Risk matrix as perceived by individuals with full colour vision, deuteranopia, protanopia and tritanopia (left to right).

Figure 2 – Choropleth map as perceived by individuals with full colour vision, deuteranopia, protanopia and tritanopia (left to right).

2. Literature Review

2.1 Information Visualization

The **definition** of Visualization is, according to the Oxford University Press, the formation of a mental image of something (Oxford University Press, 2021). Information Visualization is, as a result, the creation of a mental image based on the information that is relevant to one's search. Information Visualization typically deals with abstract data, i.e., data that has no physical referent. That is one of the biggest challenges inherent to InfoViz: to find an effective mapping between spatial representation and abstract concepts, so that the final result enables the viewer to develop insights more effectively than if they were to encounter the data in its raw state (Sorapure, 2019).

Due to the recent advances in graphic design and computer engineering, Information Visualization is often linked to the use of computer programs to display certain data. However, InfoViz does not necessarily imply the use of computer programs. As Card (2008) defines it, Information Visualization is one class of inventions for augmenting cognition. Therefore, it can have multiple forms. From a grocery list to aid memory, a map of a city's underground, to the increasingly popular statistical charts, InfoViz are new representations, procedures, or devices that augment cognition beyond its natural biological endowment. This idea that visualization is very much independent from computation is also shared by Spence (2014), who states that because visualization is, by definition, a human activity, it therefore has no relation with computers, apart from the fact that visualization can be deeply enriched through computational support. In fact, these definitions, that separate visualization from computer science, in no way question the enormous benefits than can arise from computation. Instead, they emphasise the fact that information visualization is something carried out by a human being and inevitably related to concepts such as perception and cognition, that will be addressed hereafter.

Before proceeding with this assessment, it is important to clarify one aspect, to prevent it from causing any confusion in this piece. Although Data and Information might have different meanings in what concerns cognitive, perceptual and computational spaces, during this piece these two concepts will be treated as alternative expressions in what concerns visualization. The main reason behind this choice is the fact that most of the consulted literature does not distinguish between the two terms, and often uses both in an interchangeable way when addressing visualization techniques. For a more thorough debate on this theme, Chen et al. (2009) provide an insightful article.

After all, why is visualization considered so important to augment cognition? Hutchins (1995) offers an explanation, that points out that thinking is not something that happens solely inside people's heads. Cognition is mostly done as a kind of interaction between humans and cognitive tools, that can be anything from pencils to computer-based instruments. Cognition occurs as a process in systems that contain both people and cognitive tools, as Ware (2019) reinforces. Intellectual processes in which information is obtained, transformed and used can generally benefit from using external cognition tools, as Card (2008) also points out, proceeding to list the ways in which visualization amplifies cognition, that consist of:

1. Increasing the memory and processing resources available to the users;
2. Reducing search for information;
3. Using visual representations to enhance the detection of patterns;
4. Enabling perceptual inference operations;
5. Using perceptual attention mechanisms for monitoring;
6. Encoding information in a manipulable medium.

This amplified cognition is the main reason why resorting to visualization for displaying, transmitting and understanding information is such a widely used approach. As the eye plays a major role when collecting these records, providing proper visual signals is an important step to provide better sensory inputs. The same applies to making proper Information Visualization models. Especially now, that InfoViz is becoming a mainstream medium for communicating information (Sorapure, 2019) and new ways of representing information are emerging in all sorts of contexts, guaranteeing that Information visualizations are fulfilling their function – which is to represent data in a manner that makes it easily comprehended by the viewer without going into the statistical details (Shen et al., 2019) – is crucial**.** The opportunity to create data visualizations for mainstream audiences leads to a wider range of choices, that needs to be entangled to a greater consideration of the impact of those same choices.

The previously introduced distinction between visualisation and computation aimed to provide the reader with the proper definitions of the mentioned concepts. Nonetheless, as previously stated, it is unquestionable that enormous benefits arise from combining computation with visualization, due to the vast resources that are now available to design and enhance graphic visualizations. Given where we are today, it is much more valuable to study, explore and discuss the visualization models that can be obtained using computational support than the ones that do not rely on these tools. Consequently, the scope of this work is narrowed to studying the use of computer supported visual representations of abstract data, whose use and relevance have been continuously increasing during the last decade.

As previously highlighted, visualization is a human activity. Therefore, when creating data visualizations, one must be aware of the characteristics of the human visual system. Only this way can one create appropriate representations of data, which is the ground base for the formation of proper mental images. On top of this, it is important to remember that, nowadays, the widespread use of these tools is becoming the new normal. Data graphics have become immensely popular, with innovative visualizations appearing regularly across different platforms. Consequently, visualizations can have an audience ranging from novices to experts, and need to be designed accordingly.

The ability to retrieve meaningful insights from data graphics is naturally related to the reader's ability to obtain meaning from graphs created by other people - in other words, their graph interpretation skills - but it also requires a strong set of visualisation elements. Some of these elements can be lines, dots, bars, shapes, icons, colours, thickness and textures. When one observes a visualization, a fundamental step in the process of acquiring information from it is correctly interpreting the visual marks that are being displayed and, to do this, one needs to assign a meaning to these visual cues. It is because of this reason that it is so important to think carefully about these elements, as they influence graph interpretation. Colour is a very difficult, yet unquestionably important factor in visual design. In fact, colour has been shown to promote better accuracy in map reading than gray-scale, while also being preferred over monochrome maps (Brewer et al., 1997), being definitely worth the extra effort it takes to manage it.

There are numerous advantages in using colour in InfoViz. Einakian and Newman (2019) gathered some of them while studying the suitability of certain classes of colour combinations for overlay of data attributes in map-based information visualization.

While the focus of their work is somewhat narrower, the advantages they presented can be applied to all types of visualizations, and consist of:

1. Allowing more attributes to be displayed than if only grayscale was used;
2. Allowing variation (or distinguishing levels) to be displayed in an intuitively meaningful way;
3. Possibly making structures or trends more readily discoverable;

4. Allowing annotations or labels in a different colour than the rest of the visualization.

Basically, Information Visualization relies on the usage of colour as a medium to encode and transmit meaning, acting as a new layer of complexity. Consequently, it is essential to ensure that the use of colour is suitable for transmitting the correct message when constructing a visualization, otherwise it may actually undermine the aim of InfoViz, which is to represent data in such a way that makes it more intelligible than its previsualisation. To better comprehend the theories that exist targeting the use of colour in data visualization, it is necessary to understand the concept of colour itself. The following section provides an overview of this subject.

2.2 Colour Theory

It is widely recognized that colour is a significant dimension in visual communication. In their quest for an interactive method for generating harmonious colour schemes, Hu et al. (2014) start by highlighting how colour is one of the most important, yet difficult factors in visual design. The same thinking is shared by Brockmann (1991), who supports the idea that colour is a superior visual code than shape, brightness, size or typeface, and by MacDonald (1999), who links colour importance in visual communication to its impact in the transmission of a message, reinforcing that when properly used, it can greatly enhance the effectiveness of a message, however, when used poorly it may substantially damage it.

Therefore, understanding how colour is formed, the relationships between different colours and the feelings that different colours originate in a given audience is certainly helpful to construct more effective data graphics, as well as to tackle the problems linked to colour blindness. While the physics of colour stimuli arriving at the eye can be well described, interpretation and reaction to colours are strongly marked by personal characteristics. When a word is used to identify a colour sample, it means something slightly different to each person. Colour is a subjective experience, as is endorsed by Holtzschue (2012) in her introductory colour book for designers.

Conducting scientific research on colour requires acknowledging the fact that colour varies on multiple attributes. Over the years, some experts have put forward different theories that identify these basic attributes of colours that are capable of describing them in an objective, clear way. One of them was Professor Albert H. Munsell, who created the Munsell Colour System in the first decade of the 20th Century, which Cochrane (2014) describes as being the first successful and widely accepted colour system. It is also the most used colour system in psychological research (Crozier, 1999), as its three axes match those of the human visual system very well. The Munsell Colour System is a colour order system. The logic of colour order systems is using number arrangements to identify colours, so that any unknown colour may be unambiguously placed within the system (Setchell, 2012). The system presented by Munsell has endured to the present, with some adjustments, and is still used in many industries today, providing the theoretical basis for many other modern-day colour systems. In the Munsell System every possible colour percept can be described by three dimensions:

- Hue: the general colour family cluster such as "red," "blue" or "green";
- Value (also referred to as Tone or Lightness): level of lightness or darkness of a colour sample;
- Chroma (also referred to as Saturation): the level of colour intensity or purity.

Munsell organized all the colour samples into a three-dimensional solid shape with hue, value and chroma as the three axes, as is represented in Figure 3. These attributes are the building blocks of colour and are the foundation of many colour systems based on human perception.

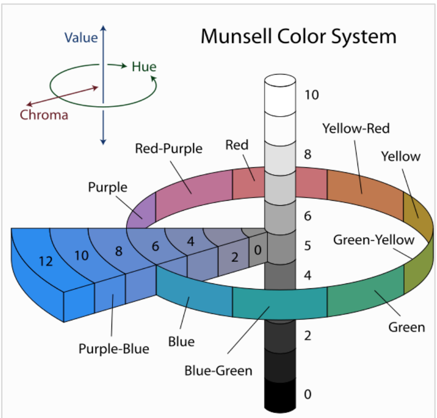

Figure 3 – Schematic diagram of the Munsell colour system. Image by Rus (2007).

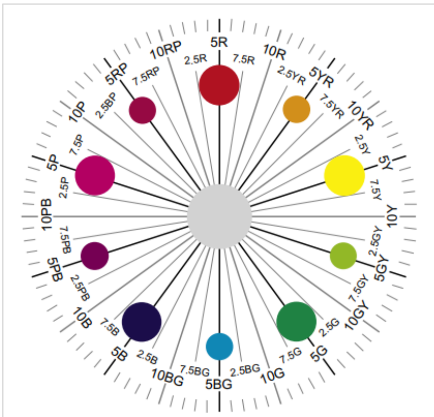

Figure 4 – Munsell's Hue circle. Image by Setchell (2012).

Circular arrangements of hues (also denominated by colour wheels) have been particularly prominent amongst theories of colour harmony. Colour harmony theories are attempts to model which colours work together visually and also provide rules on how to select harmonious colour groups. A harmonious colour scheme is generally based on geometric relationships within a colour wheel (that is not necessarily Munsell's hue circle), as well as lightness variation. Aesthetic principles for palette design are typically based on colour harmony. Monochromatic harmony schemes use colours with the same, or almost the same Hue. Analogous harmony uses colours with different, yet similar Hues. Complementary colour harmony uses Hues that are placed on opposite sides of the colour wheel.

Having this base knowledge is mandatory in order to understand the guidelines provided by many researchers to design better data visualizations, as they heavily rely on these terms to make objective suggestions that can be applied in different fields.

2.3 Colour in Information Visualization

The use of colour in data visualization serves two main purposes: it works as a decorative, aesthetic element and it acts as the primary means of informing the viewer how to interpret the displayed information, (Rigden, 1999).

Choosing the right set of colours to display information helps reducing stress (Wang et al., 2008), which is a significant factor in today's fast paced data analysis scenarios, improves performance in metrics of effectiveness, rate of task abandonment, and latency of erroneous response (Cawthon & Moere, 2007), and also promotes deeper engagement, that thus encourages the viewers to discover significant features or phenomena about the data (Einakian & Newman, 2019).

For Stone (2006), while colour has an undoubtable aesthetic component, the most important use of colour in the field of InfoViz is to distinguish different elements from each other. For this matter, the use of contrasting and analogous colours is recommended, as contrast draws attention and analogy groups. Going back to the Hue Circles presented previously, analogous colours are colours whose hues are closer in the colour wheel, while contrasting hues are situated in opposite (or sufficiently distant) sides of the wheel. In regards to Chroma, the author's advice is using colours that are darker and grayer, or closer to white (often called pastel colours). By making these choices, the obtained result is more sophisticated and allows the use of saturated colours for emphasizing certain aspects. Lastly, Value is crucial to determine the legibility of a graph. Surprising as it may seem, Value is the only key attribute for this task. Variation in Value can be used to separate overlaid elements into layers, but contrast in Hue cannot achieve the same effect.

The often-stated rule "get it right in black and white" comes from this feature of Value. Even if a design is constructed using colour, if it is built correctly, all important information can still be legible and perceivable if the Chroma is reduced to zero and only shades of gray are left. The same suggestion is shared by MacDonald (1999), who advises designers to first ensure that the layout works in monochrome (using only black, white, and grey, or using only one colour), and then adding colour cautiously to reinforce the message.

In what concerns the colour selection itself, Stone (2006) suggests that the best results are achieved when Hue is limited to a palette of two or three colours. By varying Hue and Chroma, more distinguishable colours can be created, while guaranteeing that the palette is both functional and appealing, minimizing the risk of causing visual clutter. The selection of the Hues is based on the colour harmonies addressed previously, and their positions in the colour wheel. This suggestion is in accordance with Crameri et al. (2020), Borland and Taylor Ii (2007) and Bartels and van Beurden (1998), who advise against the use of Rainbow colour maps (which are maps the vary the Hue to approximate the spectrum's visible wavelengths) and Healey (1996), whose studies on coloured target identification showed that observers have little difficulty identifying targets during the three-colour and five-colour trials, but demonstrate more difficulty during the seven and nine-colour trials. Finally, Sanocki and Sulman (2011) also performed an experiment that showed that palettes of similar colours (i.e., colours that have the same Hue) were easier to perceive and hold in visual short-term memory than palettes that incorporated colours with different Hues.

Colour's role is also crucial for enabling the user to correctly interpret the meaning of the information displayed. Therefore, the reaction and the feelings that certain colours raise in different viewers is a matter of great relevance in graphical design. The link between colour and human psychology cannot be ignored in the study of effective graphical visualization. The contribution of Bartram et al. (2017) is a good starting point to address this subject. The researchers set out three experiments to understand how different colour attributes (the formerly addressed Hue, Chroma and Value) and different palette properties promote different affective interpretations in information visualization. After obtaining the results of all the experiments, they modelled the palettes as social networks, in order to provide a better understanding of the strength and the relations between the colours. The results of the experiment make it easier to draw some conclusions about the association between colour properties and affective response. In terms of Value, there is a clear pattern: feelings as Calm, Positive, Playful and Trustworthy are associated with lightest colours, while Negative, Serious and Disturbing feelings are associated with darker tones. Chroma is higher for emotions of Excitement, Playful, Positive and Disturbing, whereas Calm, Serious and Trustworthy are associated with less saturated colours. Because there is no such clear pattern in the Hue attribute, the authors suggest that it is preferable to provide variation in Value and Chroma to express the studied feelings.

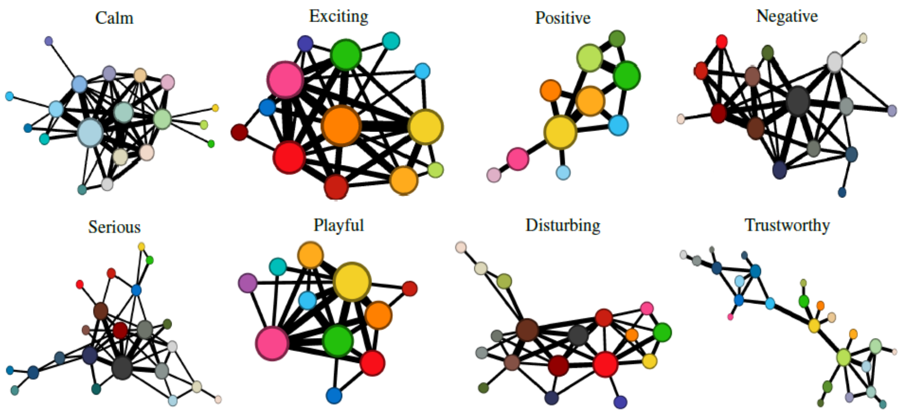

Figure 5 – Affective colour combinations displayed as networks. Image by Bartram et al (2017).

The study of Valdez and Mehrabian (1994) provided consistent evidence on how saturation and brightness have stronger effects on emotional reactions than hue. This is in accordance with a previous study about the meaning of colour, by Wright and Rainwater (1962), that also revealed that the effect of value and chroma on colour emotions was greater than that of hue.

Focusing a bit more on different hues, the review of Elliot and Maier (2014) on Colour Psychology is an insightful piece on how humans respond to different colour stimuli. They conclude that red has shown to be a critical colour. Although carrying the meaning of danger by default, in different contexts it might bring out other feelings, such as aggressiveness or failure. These feelings are associated with red's capacity of activating the nervous system activity (Kroemer Elbert et al., 2018). Other two colours the authors find worth mentioning are blue and green, as both have been shown to be associated with openness, peace, calmness and success. Bellizzi and Hite (1992) also state that red is physically and emotionally arousing and exciting, while blue is relaxing and pleasant. In his studies on colour preferences, Crozier (1999) finds that blue is consistently identified as the most preferred among all colours. The author puts forward different reasons for this pattern, which include blue being emotionally neutral and less susceptible to extremes of judgement than other hues.

A rather important point is being reached, as one of the aims of this work consists in studying and analysing how risk perception can be influenced by the use of different colours.

2.4 Risk Visualization

Risk communication often relies on the use of colour to encode and map visual parameters to numerical levels of hazard. In the last two years, motivated by the Covid-19 Pandemic, the public has seen maps, risk matrices and other types of Risk communication tools being used almost on a daily basis to depict information about the daily number of people diagnosed with Covid-19.

Although there is solid literature that targets the best practices for effectively communicating hazard information, there is limited information targeting infectious disease risk. Furthermore, given that the audience that receives this information is so heterogenous, with varied literacy levels and personal conditions, one should guarantee that the best practices possible are being applied, so that everyone can easily access this information.

For a hazard communication to be effective, firstly it needs to get noticed. Regarding noticeability, Gill et al. (1987) have shown that adding colour to a warning label can be effective in catching the user's attention. Kline et al. (1993) designed an experiment where thirty-three participants rated coloured and achromatic versions of twelve labels, having concluded that colour labels were perceived as more readable and hazardous than achromatic labels.

However much being noticed is crucial, it is not enough. It also needs to trigger the proper feelings in its audience and, as was already mentioned previously, different colours are associated with different feelings, so they must be used with care in hazard displays. There is already some research in this field. Bostrom et al. (2008) give the example of red being used to transmit danger as a robust known effect of colour, and Wogalter et al. (2002) state that the colour red is a design feature that has been found to increase hazard ratings. When performing experiments to assess whether colour of warnings affect risk perception, David Leonard (1999) examined the ways in which colour and signal words are associated to risk by members of the general public, and found that red is regarded as an appropriate colour for connoting risk at least twice as frequently as other colours. It is worth mentioning, though, that the author also suggested using other visual cues, such as geometrical shapes, as many individuals have difficulties in distinguishing colours. These findings are in accordance with Chapanis (1994), who studied the perceptions of hazard levels for different combinations of words and background colours. The three words were 'Caution', 'Warning' and 'Danger', and the background colours were white, yellow, orange and red. There was a great consistency across answers in considering the word 'Danger' and the red background as the combination that transmitted higher levels of hazard. Braun and Silver (1995) conducted a similar experiment, but besides the word and the colour, they also examined the effect of two different fonts. The interaction indicated that in conditions of reduced legibility, colour may be the only source of hazard information. The colour that conveyed more hazard was red, followed by orange, black and green.

Miran et al. (2017) compared four different schemes to illustrate probabilistic hazard information for tornado threats. The first scheme used red, orange, yellow and green to denote decreasing levels of threat; the second used a red-scale, where the value of the colour red was varied to denote different levels of probability; the third consisted on a grayscale design, that used the same value-encoding as the second scheme; and, lastly, the fourth design used contours to depict the areas of different probability levels, not using colour as a coding method. Results demonstrated that the four-colour design had the lowest average response time, suggesting that people may be more familiar with this colour combination. It was also chosen as the favourite design by the majority of the participants. The contour design took the longest time for all questions, which reinforces that the use of colour can help people in perceiving information faster.

When narrowing the research to Risk Communication for depicting the hazard of Covid-19, the available resources are naturally rarer. Even so, there are two very pertinent studies that have evaluated the effectiveness of different map designs for communicating the Covid-19 Hazard. The first one was carried out by Thorpe et al. (2021) and compared six maps with different visualization types (heat or bubble map), geographic levels (state or country) and case format (total number of cases of number of cases per capita). All maps were coloured, using a warm-coloured scheme to indicate the number of cases in different regions. Although having slight changes in the used tones, all maps relied on colours, from light yellow or light orange to vivid red or dark red, to encode the number of cases. Bubble maps used gray as the background colour. Results suggest that the simple act of providing maps with case information does not necessarily improve risk perception or public knowledge. However, when designing maps, the authors suggest that developers present cases per capita using state-level heat maps rather than country-level bubble maps.

Fang et al. (2021) produced the second of the mentioned studies. Their experiment, which is closer to what this work envisions, explored the impact of different colour schemes (cool, warm, and mixed) and data presentation forms (choropleth maps and graduated symbol maps) on comprehension and risk perception. Each participant viewed two maps, which had the same colour scheme, but different forms of data presentation (one used choropleth maps, while the other graduated symbol maps). Some of the utilized measures consisted of eye-tracking measurement, accuracy rate, risk perception and subjective satisfaction. Results showed that the use of a warm colour scheme has an advantage in terms of attractiveness, while the mixed-colour scheme scored the lowest in this measure. However, they also revealed that, in terms of accuracy, the mixed colour maps had statistically best performance than the two other schemes. This result is both in line with theories that support that varying the Value and Chroma produces more pleasing visualizations than varying the Hue (Stone, 2003) and with the ones that suggest that mixed-colour schemes are processed faster because, when colour coding is familiar users can more easily interpret the information it depicts (Glazer, 2011). When it comes to the data presentation forms, results showed that this variable significantly affects risk perception of Covid-19 maps, as the choropleth maps had superior risk expressiveness than the graduated symbols maps. They concluded that both colour schemes and data presentation forms can influence risk communication of Covid-19 maps.

2.5 Colour blindness

Colour blindness is the reduced ability to perceive or differentiate colour (Ahmed et al., 2020). It is a disorder that has many nuances and degrees, and across all its levels, it affects about 8% of the male population and 0,4% of the female (Keene, 2015). Because it is classified as a mild disability, the challenges that this group of people face are often overlooked; however, in their everyday lives, colour-blind people encounter a series of challenges that those without vision impairments might not be sensitive to. Emmenegger et al. (2014) have listed some of them while interviewing colour-blind participants, and simple activities such as choosing clothes, telling the doneness of meat while cooking and differentiating the colours of signal lights while driving were identified as challenging situations for this group of people. The need for creating maps and information graphics that account for this vision impairment has already been noticed by some authors (Brewer et al., 1997; Crameri et al., 2020; Engeset et al., 2022). Before addressing some guidelines for preparing colour-blind friendly figures, a basic understanding of the human eye anatomy and of the different types and degrees of colour blindness is helpful.

One of the elements of the human eye is the retina, a light-sensitive tissue lining the back of the eye that receives light and converts it in into energy that is transmitted to the brain

(Perkins & Davson, 2021). The light is captured by photoreceptors, which are subdivided into two classes: rods and cones. The rods cells are responsible for monochromatic vision in situations of dim light, functioning at low levels of illumination. The cone cells function best at high levels of illumination and are the main responsible for colour vision. Because cones are not stimulated by low light levels, night vision is a function of the rods, which is why it is mostly devoid of colour (Keene, 2015).

Human colour vision is Trichromatic. This means that the eye possesses three classes of cone photoreceptors. The photoreceptors are all sensitive to a wide range of wavelengths, and as each cone responds to a broad range of wavelengths with overlapping ranges, the three photoreceptors cover the full visible spectrum. Nevertheless, different types of cones have a maximal sensitivity for different wavelengths (Pouli et al., 2016). The cones that are the most sensitive to the longest wavelengths are also the most sensitive to the colour red; the ones that are the most sensitive to the medium wavelengths are the most sensitive to the colour green, and lastly, cones that have the maximal sensitivity to short wavelengths are the most sensitive for the colour blue (Choudhury, 2014). Impairments in colour vision are caused by the absence or mal-functioning of (at least) one of the photoreceptors cones. Colour blindness types and degrees are associated with the absence or weakened sensitivity of one or more of these types of cones. The terms '*prot*', '*deuter*' and '*trit*' are used as prefixes for denoting impairments in the cones sensitive to longest, medium and shortest wavelengths, that correspond to red-sensitive, green-sensitive and blue-sensitive, respectively.

Anomalous Trichromacy happens when the three types of cone receptors exist in the human eye, but one of them is less sensitive than the two others. There are three forms, depending on the type of receptor that is damaged:

- Protanomaly: having a mutation in the long-wavelength (red) pigment;
- Deuteranomaly: having a mutation in the medium-wavelength (green) pigment;
- Tritanomaly: having a mutation in the short-wavelength (blue) pigment.

Dichromatism occurs when one of the three cells is missing, and the human eye relies only on the two other cones to perceive colour. Once again, there are three forms that depend on the type of cell that is missing:

- Protanopia: the red-sensitive cone is missing, and the colours between the green-yellow-red section of the spectrum are affected;

- Deuteranopia: the green-sensitive cone is missing, and the colours affected are again the ones in the green-yellow-red section of the spectrum;
- Tritanopia: the blue-sensitive cone is missing, and the colours along the blue-yellow section of the spectrum are affected.

When only one type, or actually none of the cones are present, Monochromacy occurs, that leads to the incapacity of perceiving any colour, resulting in a gray-scale type of vision.

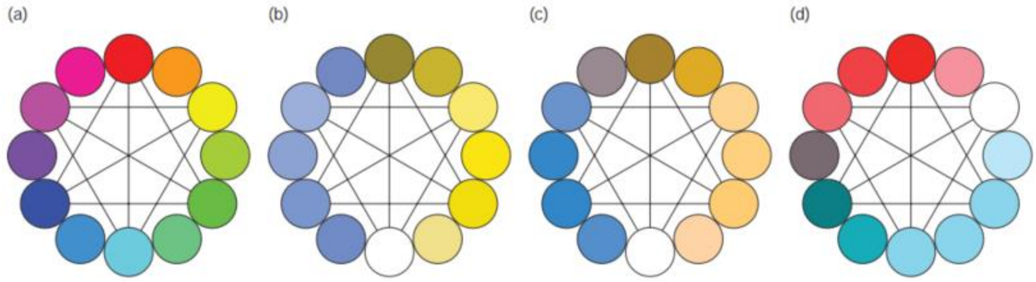

Figure 6 – Colours of the hue circle as perceived by individuals with full colour vision, protanopia, deuteranopia and tritanopia (left to right). Image by Choudhury (2014).

Because the sensitivity curves of the green and red cones are closer to one another, impairments in these cones cause relatively similar changes in the way that colour is perceived (although not exactly the same). In terms of affected population, Deuteranomaly has the highest occurrence, affecting approximately 4.9% of men and 0.38% of women. Protanomaly, Protanopia and Deuteranopia have similar average occurrence rates, that all approximate to 1% of men and 0.02% of women. Tritanopia has the lowest prevalence, affecting around 0.002% of men and 0.001% of women. The prevalence of Tritanomaly is unknown (Choudhury, 2014), but it is a rare condition (Emmenegger et al., 2014).

In a nutshell, colour blindness can be categorised into two main groups: Red-Green colour blindness, that has the highest prevalence and is associated with damages in the red and green sensitive cones and Blue-Yellow colour blindness, that is associated with defects in the blue sensitive cone and affects a smaller percentage of the population.

2.6 Guidelines for creating colour-blind friendly visualizations

Figure 6, which displays how hue circles are perceived by observers with different types of colour blindness, is a good starting point for understanding their difficulties when visualizing data in form of graphical information. Ensuring that graphical visualizations are designed for universal legibility should be something endorsed by authors and publishers (Crameri et al., 2020). This can be achieved by following guidelines for preparing figures that are accessible to colour-blind individuals. In this line of thought, some suggestions have been presented.

Keene (2015) suggests, in the first place, simulating how an image is perceived by colour-blind people, to evaluate its accessibility before its publication. He then proceeds to suggest replacing red for magenta (magenta is the equal mixture of red and blue) in red/green images, so that the two colours are discernible for the whole audience. A simulation of a line graph using the colours black, yellow, green, magenta, and dark blue showed that this colour combination is distinguishable by deuteranopes and tritanopes, but protanopes still face some struggles with this palette. Therefore, it is very helpful to designate the identity of each line with an arrow, pattern or texture, so that colour is not the only key element. Colour, as the author sees it, should be a useful (to the colour sighted) but unnecessary (for the colour impaired) element to grasp the content of a graph.

Okabe and Ito (2002) also share the advice of replacing red with magenta in red-yellow-green pictures and of not relying uniquely on colour to convey information. They recommend using differences both in colour and in shape, keeping the number of colours to a minimum, controlling contrast not only in hue but also in brightness (value) and making it possible to communicate without using colour names. They conclude by providing a colour palette that is friendly for full colour and colour-impaired vision individuals. Vermilion is used instead of red, colours between yellow and green are avoided, blueish green is chosen rather than plain green, reddish purple is chosen over violet and sky-blue and blue are both included as their differences in brightness and saturation makes them easily distinguishable for all vision types. When combining colours from the suggested palette, it is advised to use warm and cool colours alternatively. Jenny and Kelso (2007) recommend the *ColorBrewer* online tool to help choose universally accessible colour schemes for maps. Colours with strong contrast and complementary visual variables (such as the previously mentioned shape, size and pattern) help readers interpreting and perceiving symbols more easily. Other practices include simplification of the map design and availability of annotations directly in the map in spots where the reader might misinterpret the information. Roskoski (2017) discourages the use of red and green close to each other, because of protanopes' and deuteranopes' difficulty in distinguishing these colours. He advises the use of monochromatic palettes, as black, gray and white are easily distinguishable by nearly everyone. When using colour, the best choice according to the author is using blue, because, as he states, blue is perceived uniformly as a colour by all individuals. It is followed by yellow, but depending upon the background of the image. The author also subscribes the recommendation of using magenta (or another off-red colour) instead of red. Brewer (2006) advises against the use of multiple hues when designing maps, given that colour-blind readers have trouble distinguishing some tones. The author also recognizes that spectral (rainbow schemes that include all high-saturation colours of the spectrum) and red-yellow-green schemes, although popular, are difficult to read for people with colour vision deficiencies.

Finally, Ichihara et al. (2008) have put forward a colour palette that contains four easily distinguishable colours for all vision types. These colours consist of Black, Vermillion, Blueish-Green and Blue. This palette was constructed to be applied to timetables for the Tokyo subway system map to indicate different train lines. Although their study concluded that, by carefully selecting hues within the range of each colour category, it is possible to establish colour combinations which are easily distinguishable for everyone, the reliance on colour only is discouraged whenever possible.

2.7 General discussion

After this review, one can see that there is a conflict between the most used colour schemes for displaying risk information and the guidelines for designing colour-blind friendly figures. This conflict has been noticed by some organizations, such as the European Centre for Disease Prevention and Control. In fact, in their weekly publications of updates in Covid-19 Maps in support of the Council Recommendation on a coordinated approach to travel measures in the EU, they provide two different maps for displaying the same information: a standard one, designed with a colour scale that uses green-yellow-red coloured-schemes, and a colour-blind friendly one, that uses blue with different lightness levels to indicate the level of risk of each country.

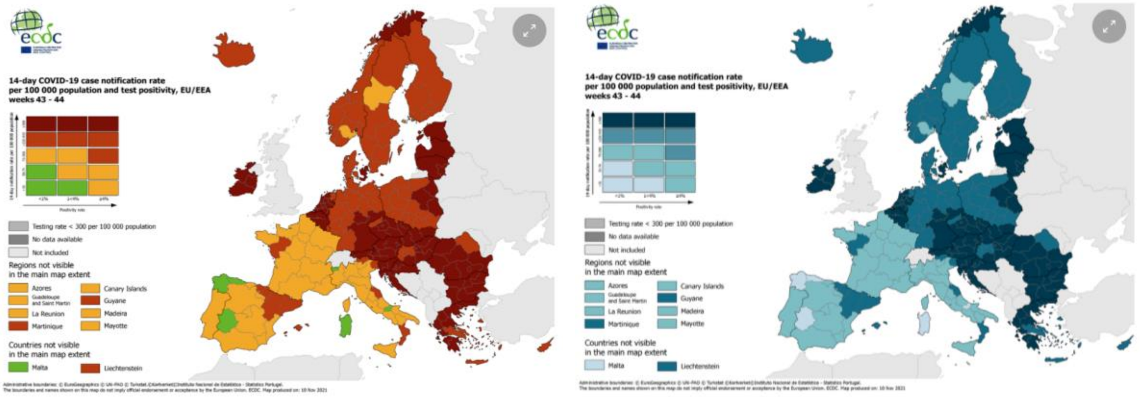

Figure 7 – Choropleth maps displaying the ECDC Combined Indicator. On the left, a standard one; on the right, a colour-blind friendly one.

This approach is an excellent example of how risk communication should be transmitted to its audience. However, it does not happen frequently. Taking as an example the Risk matrix used by the Portuguese Government for displaying the Transmissibility Rate and the Number of New cases in the last 14 days by 100 000 habitants, a colour palette based on the red-yellow-green scheme is the main resource for depicting the level of current risk of the country. This can cause trouble for colour-blind individuals (especially Deuteranopes and Protanopes), as they may perceive lighter sections of the image as less risky, which is not an accurate interpretation of the risk matrix. The same happens with various choropleth maps that also resort to this colour-scheme to showcase distinct risk levels between several cities. Based on the reviewed literature on the affective role of colour, risk visualization and colour-blind friendly figures, an alternative colour palette to use in visualizations targeting infectious disease risk is suggested and its effectiveness is evaluated.

3. Experiment Design

The questions this work aims to answer are the following:

1. Are the visual representations of data for depicting the risk associated to the Covid-19 Pandemic effective for individuals with colour vision deficiencies?
2. Are there alternative colour-schemes that better serve the colour-deficient population without damaging the interpretation of full-colour vision individuals?

This study investigates the effects of two different colour schemes for displaying Covid-19 related information, namely red-green colour scheme and blue-gradient colour-scheme, on users' graph comprehension, risk perception, intention to adhere to infection control guidelines and overall satisfaction.

The goal of the current experiment is to assess what colour scheme helps colour-vision impaired individuals make the most accurate judgements regarding Covid-19 related information while assessing how full colour vision individuals react to a new colour-scheme to depict risk information. Therefore, individuals with and without colour vision impairments were recruited to participate in the experiment, and were assigned to one of two groups: the red-green group and the white-blue-black group.

The study was conducted using web-based surveys and had the approval of both the Ethics Committee of the University of Porto (Report Nº128 /CEUP/2022) and the Data Protection Unit of the University of Porto (Report R-4/2022).

The two colour schemes, applied to two different graphical visualizations, were tested on a total of 161 participants, 81 with full colour vision and 80 with colour vision deficiencies. From the 81 participants with full colour vision, 43 were assigned to the white-blue-black gradient group and 38 were assigned to the red-green one. From the 80 participants that reported having some type of colour blindness, 47 viewed the white-blue-black gradient group, and the remaining 33 saw the red-green one. Sections that follow provide descriptions of the colour schemes, the visual representations, the sample, the test questions and the testing procedure. The complete survey, including the introduction, instructions and all of the questions can be found in the Annex (see Figures 26 to 37).

3.1 Colour Schemes

Two colour schemes were studied in this experiment: a diverging colour scheme and a sequential colour scheme. The diverging colour scheme consisted of a green-red scheme, and the sequential colour scheme consisted of a white-blue-black one

Diverging colour-schemes are multi-hue sequences, suitable for when critical data classes or break points need to be highlighted. Although this case is not of such nature, the green-red diverging colour scheme is included as it is commonly used for portraying risk information, as was the case for the Risk Matrix adopted by the Portuguese Ministry of Health. In fact, the colour palette was obtained by using RStudio (RStudio Team, 2022) to extract the colours employed in this visualization, more specifically by using the packages *magick* (Ooms, 2021) and *imager* (Barthelme, 2022) to load, resize and quantize the image.

Sequential colour schemes imply order, being appropriate for displaying data that ranges from low-to-high values (Harrower & Brewer, 2003), which perfectly fits the nature of Covid-19 related information, as low values of new cases indicate lower risk, while higher values indicate a riskier situation. In this case, the tested palette goes from light-to-dark colours for low-to-high risk, following the design convention that 'light is less – dark is more' (Garlandini & Fabrikant, 2009). The colour scheme that served as a basis for this sequential white-blue-black palette was *Oslo,* from R package *colorspace* (Zeileis, 2009). *Oslo* colour palette was created by Crameri (2018) in his quest for creating scientific colour-schemes. It is a perceptually uniform, colour-blind friendly palette, and because the only hue it uses is blue, it benefits from the advantages explored in the previous section related to using this hue. Some specifications of this palette were selected using the *choose_palette()* function, also available in *colorspace* (Zeileis, 2020).

The two colour-schemes are shown in Figures 8 and 9. Their hexadecimal codes and their HCL (hue-chroma-luminance) representation, obtained by using R package *farver* (Lin Pedersen, 2021) can be found in Tables 17 and 18.

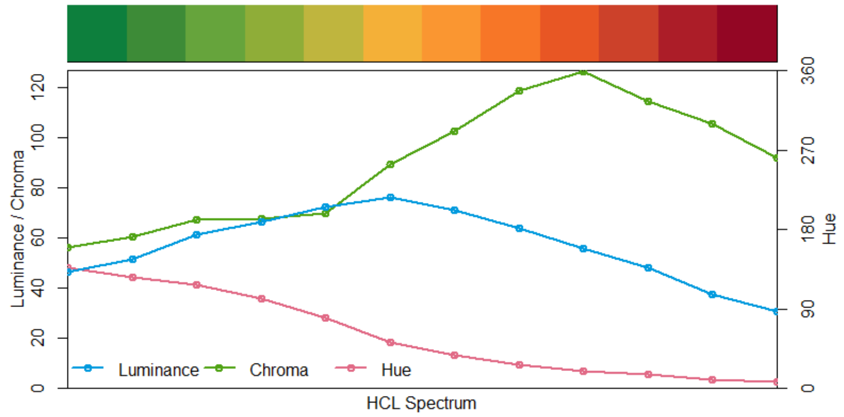

Figure 8 – Green-red palette representation in the Hue-Chroma-Luminance coordinates.

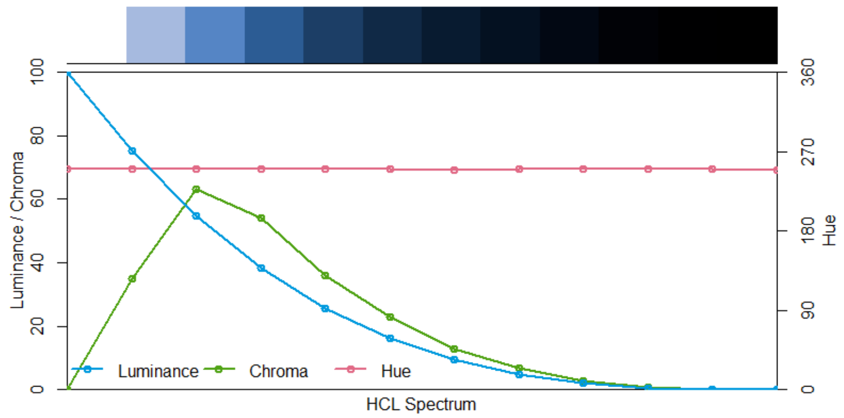

Figure 9 – Gradient blue palette representation in the Hue-Chroma-Luminance coordinates.

3.2 Visual Representations

Two different visual representations were chosen for testing the previously shown colour schemes: a choropleth map and a risk matrix. Choropleth maps offer an intuitive and easy way to assess how a certain variable varies across a given region. In this case, the variable was the severity of the Covid-19 Pandemic. These maps were chosen because of the important role that geospatial information systems (GIS) have played in providing rapid visualizations of the spread of the Covid-19 pandemic, predicting regional transmission and helping decision-makers build better responses to the global pandemic (Rosenkrantz et al. (2021); Zhou et al. (2020); Juergens (2020)). The choice to also include a risk matrix was driven by the fact that this particular form of visualization was adopted by the Portuguese Ministry of Health to track the evolution of the pandemic, especially during the year of 2021. The risk matrix displays the Transmissibility Rate on the horizontal axis and the Number of New cases in the last 14 days by 100 000 inhabitants on the vertical axis. Points are drawn inside the Matrix, to indicate the level of severity of the Pandemic situation in a given time, indicated by the variables of the x and y axis. It was a useful tool to evaluate the evolution of the pandemic in a certain period, as multiple points could be laid out, allowing one to compare the different pandemic stages.

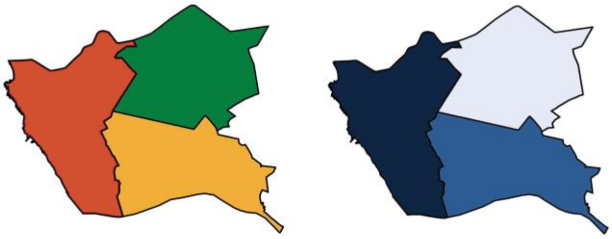

Figure 10 – Choropleth maps used in the experiment. On the left, the green-red; on the right, the gradient-blue.

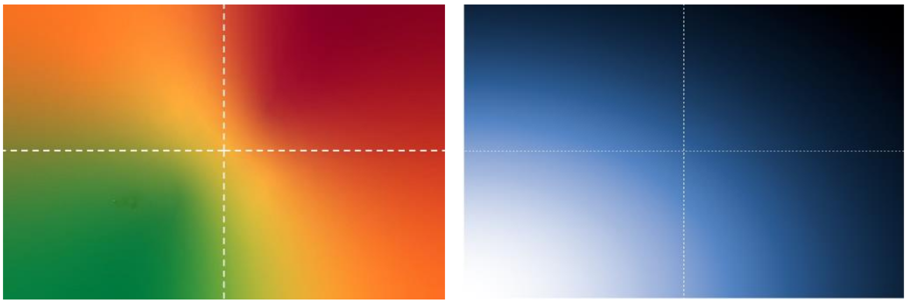

Figure 11 – Risk matrices used in the experiment. On the left, the green-red; on the right, the gradient-blue.

3.3 Participants

This study collected data from 161 participants who were randomly recruited from Prolific, a platform that connects researchers with their target participants around the world. The selection of participants is made by the platform using pre-screening filters, to ensure that the researcher finds a suitable sample for their study. The participation is voluntary, and participants were paid for their participation in the study, according to Prolific's payment policies. Sociodemographic questions were limited to age, gender, highest level of education, and whether they experience colour blindness or not. Each participant is only identified by an alphanumeric code assigned automatically and randomly by Prolific.

To be eligible to participate in the study, subjects had to meet all the following requirements: be at least 18 years old, have a good command of the English language and not reside in Portugal. This last requirement was included in order to avoid gathering participants who were already familiar with the risk matrix.

From the 161 participants, 98 were male (60,87%), 61 were female (37,89%), 1 was nonbinary (0,62%) and one participant opted for not answering this question. Participants' ages ranged from 18 to 66 years old, with an average age of 28 years old (SD = 8.8). Educational levels also varied from Primary School to Doctorate Degree. 12 (7,45%) of the 161 subjects work frequently with data visualization and graphical design, while 69 (42,86%) do it only occasionally and 80 (49,69%) affirmed never doing it.

3.4 Test Questions

The questions of the experiment were divided into three different categories: interpretation, risk perception and satisfaction and preference. All questions were accompanied by some sort of visual element, and participants could make their judgments about the questions while seeing the visual representations that were being studied.

The interpretation questions aimed to evaluate participants' accuracy and efficiency of comprehension. All questions were multiple choice, with one or two correct answers. Correct answers were assigned 1 point, while wrong answers were assigned 0 points.

Table 1 – Questions for measuring participants' accuracy of interpretation.

Question	Question Description	Visual Element	Underlying Task	Answer Type
Q1	Which of the cities do you think is in a riskier situation?	Choropleth Map	Comparison and value retrieving	Multiple choice
Q2	Which of the cities do you consider to be in the safest situation?	Choropleth Map	Comparison and value retrieving	Multiple choice
Q3	In which of the selected points is the risk associated with the Covid-19 Pandemic higher?	Risk Matrix	Comparison and value retrieving	Multiple choice
Q4	If the Pandemic situation were to change from point C to point D, would you consider that the gravity of the pandemic situation has…	Risk Matrix	Comparison and evolution interpretation	Multiple choice

Participants then advanced to the risk perception section, which consisted of two questions.

Table 2 – Questions for measuring participants' risk perception.

Question	Question Description	Visual Element	Underlying Task	Answer Type
Q5	Imagine that the pandemic situation in the country where you live is represented by point E. On a scale from 1 (not risky at all) to 5 (very risky), how risky would you perceive the pandemic situation to be?	Risk Matrix	Perform judgement about the severity of a risk	5 Point Ordinal Scale
Q6	Imagine that the pandemic situation in the country where you live is represented by point E. On a scale from 1 (no intention at all) to 5 (very strong intention), how strong would your intention be to adhere to Covid-19 health-related guidelines?	Risk Matrix	Perform judgement about protective behaviour	5 Point Ordinal Scale

Lastly, they answered the satisfaction and preference questions.

Table 3 – Questions for measuring participants' satisfaction and subjective preference.

Question Description	Visual Element	Underlying Task	Answer Type
How satisfied do you feel with the map that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic of multiple cities? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied).	Choropleth Map	Map rating in terms of subjective satisfaction	5 Point Ordinal Scale
How satisfied do you feel with the graph that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied).	Risk Matrix	Matrix rating in terms of subjective satisfaction	5 Point Ordinal Scale
Which, from these two maps, is your favourite for depicting different degrees of the risk associated to the Covid-19 Pandemic between multiple cities?	2 Choropleth Maps	Choice between Red-Green and Blue-Gradient choropleth maps, in terms of personal preference	Multiple choice
Which, from these two graphics, is your favourite for depicting the risk associated to the Covid-19 Pandemic?	2 Risk Matrices	Choice between Red-Green and Blue-Gradient risk matrices, in terms of personal preference	Multiple choice

The complete survey, including all the questions, visual representations and possible answer options can be consulted in the Annex.

3.5 Procedure

In this experiment, two studies were implemented on Prolifc. One of the studies targeted participants with full colour vision, while the second one targeted participants with some type of colour blindness. The pre-screening was made by asking the participants the following question 'Do you experience colour blindness?'. The first study gathered answers from participants who answered 'No, I have no issues seeing colours', while the second one recruited users who had answered 'Yes, I'm colour-blind.' to the question.

To those participants that met all the requirements to participate in the studies, a link redirecting them to a Survey was made available. When clicking on the link, the participants were redirected to a formR survey, where they were requested to insert their Prolific ID in order to proceed. After inserting the ID, formR randomly redirected them to one of the two JotForm surveys – the one featuring the Green-Red colour scheme or the Blue-Gradient one. Using formR was the most convenient way of randomly assigning the participants to each of the surveys. When in Jotform, participants would first view an Introductory page, that contained general information about the study they were about to participate in. It included the context and the objectives of the study, the eligibility of the participants, the risk and the benefits associated with participation in the study, the confidentiality and data protection policy, the purpose of data processing and the possible dissemination of results for scientific matters. To advance to the experiment itself, participants had to click a button that stated that they had carefully read the information provided and were eligible to participate in the study, so it is assumed that all the participants have read the relevant information about the purpose of data collection, processing and storage, and dissemination of results, and gave their informed and voluntary consent to participate in the study. Participants were also informed about what type of tasks they would be performing and advised to answer the questions as quickly as possible, without thinking too much.

After answering all the questions of the survey, participants were asked if there was any comment they would like to leave. When clicking the 'Submit' button, they were redirected to a Prolific page, intended to prove that the participants completed the study. There were no restrictions regarding what kind of device the participants could use to answer the survey.

4. Results

Different approaches were used to explore the results of the experiment, given that the interpretation questions produced a binary outcome, based on whether the participant's answer was right or wrong, and the risk perception and satisfaction questions produced an ordinal outcome, as these were questions of subjective scale.

Interpretation questions had two possible outcomes: being correct or incorrect. Therefore, logistic regression in the form of generalized linear models was used to analyse these results, given that it is suitable for modelling the relationship between the expected value of a binary variable and a combination of explanatory variables. The independent variables were the colour scheme (with two factors: blue and green-red) and the vision type (with two factors: full colour vision and colour blindness). This analysis was carried out using *glm*() command from R package *stats* (R Core Team, 2020). The default link function in *glm()* for a binomial outcome variable is the logit. In logistic regression, the predictors' coefficients indicate the expected change in log odds of having a successful outcome (i.e., of correctly answering the questions) associated with a unit change in the predictor. In this case, because the model deals with binary categorical variables only, the change in log odds is associated with going from 0 to 1 in that variable.

Risk perception and satisfaction questions were measured with a 5-point ordinal scale. Although many studies use metric models to analyse ordinal data, this approach is not recommended as it can lead to Type I errors (detection of effects that do not exist) and Type II errors (failures to detect effects) (Liddell & Kruschke, 2018). Thus, Ordinal Regression models with the proportional odds assumption were used instead, through R's package *ordinal* (Christensen, 2019). Ordinal Regression models (also referred to as Cumulative Link Models) correctly treat ordinal data as categorical and allow for its ordered nature to be exploited, which makes them a powerful model for such data (Christensen, 2018).

The following equations show the general equations of the two types of implemented models.

The log odds of a correct answer to the proposed questions are estimated by the logistic regression represented by equation (1).

$$log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 \times Blue + \beta_2 \times Colourblind + \beta_3 \times Blue \times Colourblind \quad (1)$$

The probability of a correct answer to the proposed questions is given by equation (2).

$$P = \frac{e^{\beta_0 + \beta_1 \times Blue + \beta_2 \times Colourblind + \beta_3 \times Blue \times Colourblind}}{1 + e^{\beta_0 + \beta_1 \times Blue + \beta_2 \times Colourblind + \beta_3 \times Blue \times Colourblind}} \tag{2}$$

The log odds of an observation falling in the jth category or below are estimated by the ordinal regression equation represented by equation (3).

$$\log\left(\frac{P(Y \leq j}{1 - P(Y \leq j)}\right) = \theta_j - \beta_1 \times Blue + \beta_2 \times Colourblind + \beta_3 \times Blue \times Colourblind \tag{3}$$

$$j = 1,2,3,4,5$$

The Cumulative probability of an observation falling in the jth category is estimated by equation (4).

$$P(Y \leq j) = \frac{e^{\theta_j - \beta_1 \times Blue - \beta_2 \times Colourblind - \beta_3 \times Blue \times Colourblind}}{1 - e^{\theta_j - \beta_1 \times Blue - \beta_2 \times Colourblind - \beta_3 \times Blue \times Colourblind}}, \tag{4}$$

$$j = 1,2,3,4,5$$

All the models (generalized linear models and cumulative link models) were configured to use an interaction between the variables colour scheme and vision type, to assess not only each main effect of the two variables on the dependent variables, but also if one of the variables influenced the effect of the other on the target variable. The reference levels for the models, that are chosen to be the reference so that all odds ratios are a comparison to the reference group, were the green-red colour scheme and the full colour vision type.

The analysis of the results includes, for each question, a table summarizing the parameter estimates, their standard errors, the odds ratio obtained from the estimates, the 95% confidence interval for the odds ratio and the Wald based *p-values* for tests of the parameters being zero (in other words, their significance level). Questions analysed using Cumulative Link Models also include a table with the different threshold coefficients. Tables with the predicted probabilities associated to each model (fitted for each question) can be found in the Annex. Graphical visualizations in the form of bar charts are also included, and were obtained by using the packages *ggplot2* (Wickham, 2016), *ggeasy* (Carroll, 2021) and *gridExtra* (Auguie, 2017). Package *emmeans* (Lenth, 2022) was used to obtain the displayed 95% confidence intervals. The colours used in all these graphs were selected from colour-blind friendly palettes, available in packages *viridis* (Garnier, 2018) and *ggokabeito* (Barrett, 2021), and package *colorblindr* (D. McWhite, 2022) was used to simulate how the produced graphs were perceived by colour blind individuals.

4.1 Effect on Interpretation accuracy

The proportion of right answers by group and by colour scheme regarding the first interpretation question is presented in Figure 12. The question asked participants to identify the city they considered to be in a riskier situation from a total of three cities.

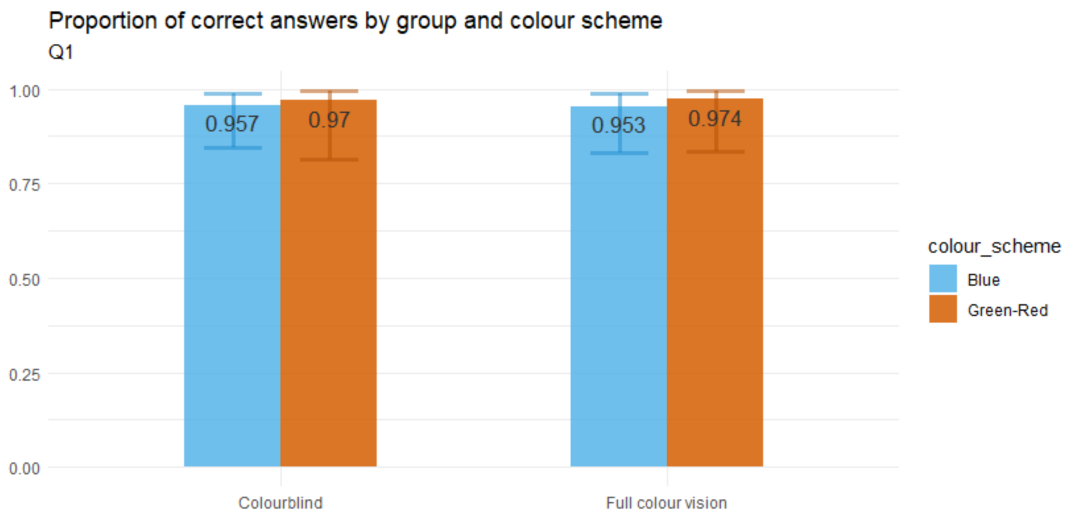

Figure 12 – Proportion of correct answers by group regarding the first choropleth map question.

Table 4 – Logistic Regression results for the first choropleth map question.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
(Intercept)	3.611	1.013	36.99	[5.0767;269.66]	3,66E-04
Blue	-0.591	1.246	0.554	[0.0482;6.3653]	0.635
Colour blindness	-0.145	1.435	0.865	[0.0519;14.394]	0.919
Blue*Colour blindness	0.238	1.762	1.269	[0.0401;40.125]	0.892

The results were very positive for all the subgroups, as more than 95% of the participants allocated to each group answered correctly. The logistic regression output shows that the blue colour scheme negatively impacts the probability of correctly answering for full colour vision participants – the associated odds decrease by approximately 44.6% when compared to the green-red colour scheme. Colourblind participants have approximately 13.5% lower odds of correctly answering compared to full colour vision participants, when the colour scheme is the green-red one. Lastly, the interaction between being colour-blind and viewing the blue colour scheme is positive, which indicates that if the viewer is colour-blind, the effect of viewing the blue palette is not as negative as it is for full colour vision users. In this case, the odds of a colourblind participant answering correctly with the blue colour scheme are around 30% lower than the odds of a colourblind participant that sees the green-red scheme. Both the estimates as the interaction between them are non-significant ($p > 0.05$).

The second question asked participants to identify the city they considered to be in the safest situation.

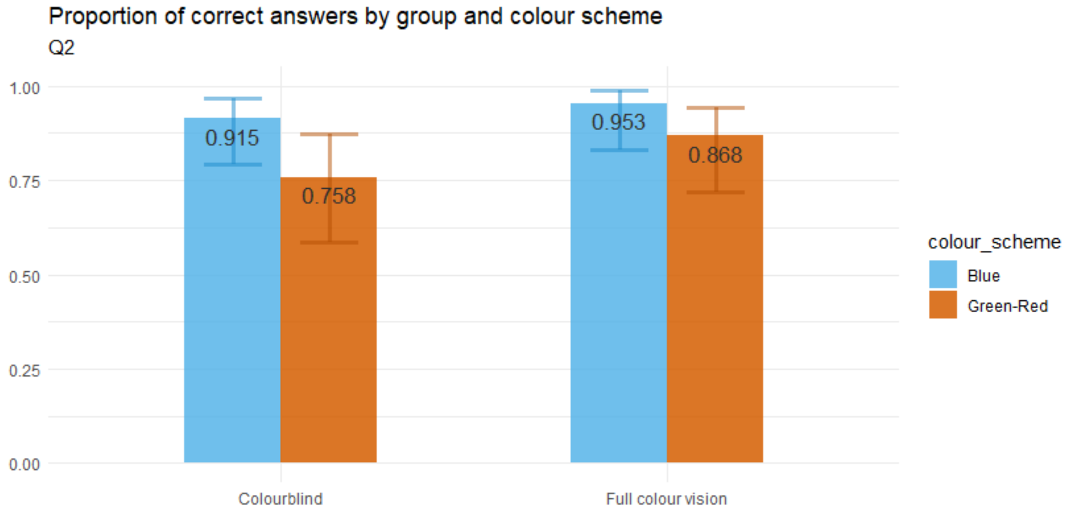

Figure 13 – Proportion of correct answers by group regarding the second choropleth map question.

Table 5 – Logistic Regression results for the second choropleth map question.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
(Intercept)	1.887	0.480	6.600	[2.5766;16.906]	8,42E-05
Blue	1.133	0.869	3.106	[0.5659;17.048]	0.192
Colour blindness	-0.748	0.629	0.474	[0.1380;1.6236]	0.234
Blue*Colour blindness	0.102	1.092	1.107	[0.1302;9.4197]	0.926

The percentage of participants who chose the correct option in the second option is lower than in the first one. 88.2% of the participants chose the correct option. The blue colour scheme affects positively the odds of a correct answer for both groups: full colour vision participants have 210% higher odds of answering correctly with the blue colour scheme than with the green-red, and as for the colourblind participants, this percentage is fixed at 240%. Furthermore, the odds of answering correctly are 53% lower for colourblind participants who see the green-red colour scheme than for full colour vision participants with the same palette. However, and again, neither the estimates nor the interaction between them were significant ($p > 0.05$).

The third question asked participants to compare the severity between two points inserted in the risk matrix.

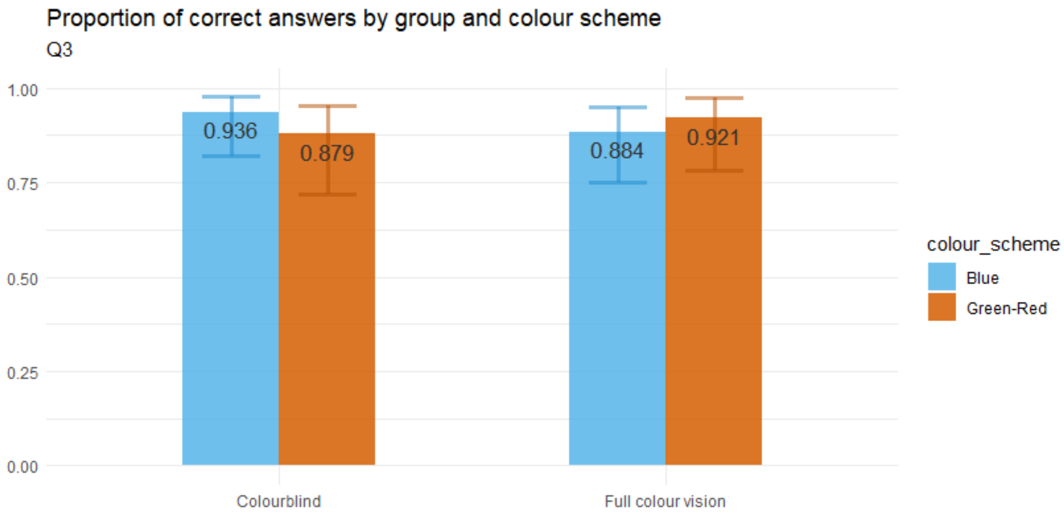

Figure 14 – Proportion of right answers by group regarding the first risk matrix question.

Table 6 – Logistic Regression results for the first risk matrix question.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
(Intercept)	2.457	0.602	11.666	[3.5878;37.933]	4,00E-05
Blue	-0.427	0.767	0.653	[0.1451;2.9344]	0.576
Colour blindness	-0.476	0.804	0.621	[0.1285;3.0045]	0.554
Blue*Colour blindness	1.133	1.109	3.106	[0.3536;27.271]	0.307

For full colour vision participants, the blue colour scheme resulted in 34.7% lower odds of correctly answering this risk matrix question. For colourblind participants, the odds of answering correctly are 103% higher when viewing the blue colour scheme. When viewing the green-red scheme, colourblind participants have 37.9% lower odds of answering correctly when compared to full colour vision participants. The coefficients' estimates and the interaction between them are non-significant ($p > 0.05$).

The fourth and last interpretation question asked participants to classify the Covid-19 pandemic evolution based on two different points drawn inside the risk matrix, that represented two distinct stages of the pandemic.

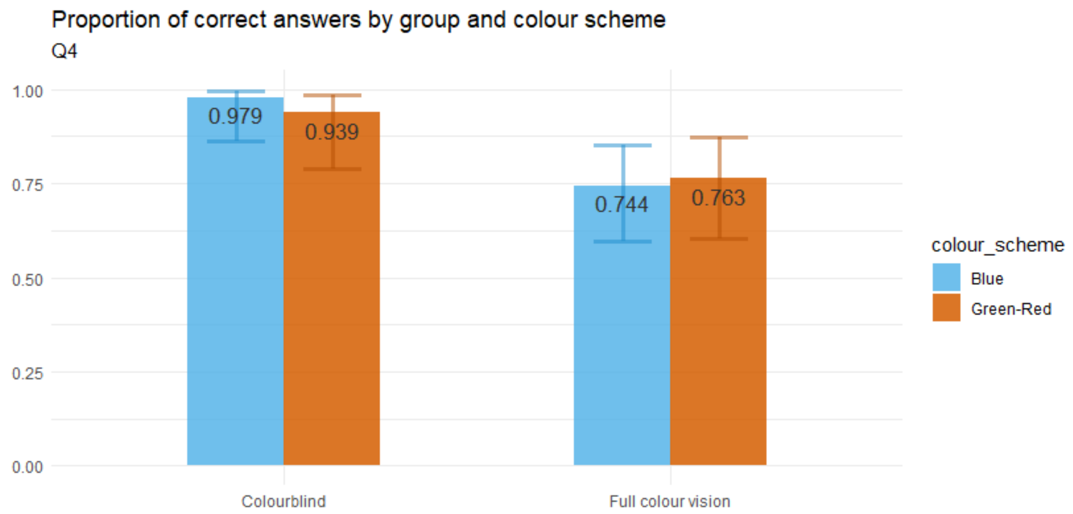

Figure 15 – Proportion of correct answers by group regarding the second risk matrix question.

Table 7 – Logistic Regression results for the second risk matrix question.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
(Intercept)	1.170	0.382	3.222	[1.5252;6.8075]	2,17E-03
Blue	-0.102	0.517	0.903	[0.3274;2.4890]	0.843
Colour blindness	1.571	0.823	4.810	[0.9580;24.154]	0.056
Blue*Colour blindness	1.190	1.350	3.287	[0.2333;46.312]	0.378

Overall, this was the question with worse results: 85.7% of the participants answered correctly. This was the only of the four questions where being colourblind has a positive effect in the odds of correctly answering with both colour schemes: it increases the odds by approximately 380% when the colour scheme is the green-red one and by 1481% for the blue-gradient one. The blue-gradient colour-scheme had a negative effect for the full colour vision group, decreasing the odds of correctly answering by approximately 9.7% compared to the green-red scheme, and a positive effect for the colourblind group, increasing the odds of correctly answering by approximately 197%. The p-values for the estimates and their interaction were bigger than 0.05.

Lastly, the average proportion of right answers obtained by the participants of the different groups can be viewed on Figure 16.

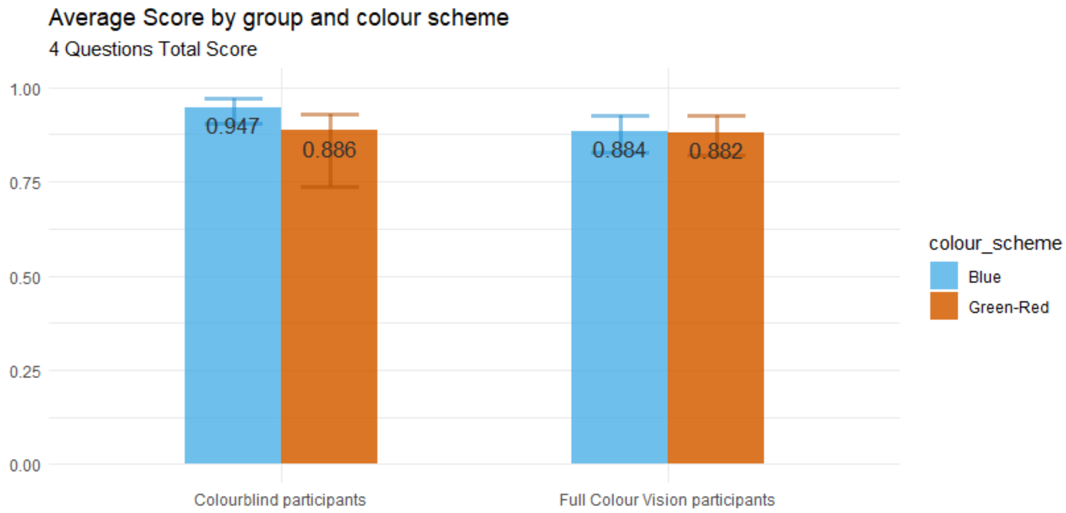

Figure 16 – Average proportion of correct answers of the 4 interpretation questions, by group.

Table 8 – Logistic Regression results for total score.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
(Intercept)	2.007	0.251	7.444	[4.5514;12.176]	1,28E-15
Blue	0.047	0.372	1.048	[0.5055;2.1714]	0.900
Colour blindness	0.021	0.346	1.021	[0.5183;2.0107]	0.952
Blue*Colour blindness	0.804	0.548	2.235	[0.7634;6.5448]	0.142

To analyse the total score, the argument *weights* of the *glm* command was set to 4 (the total amount of interpretation questions), to provide the number of trials, given that the response variable is the proportion of successes (R Core Team, 2020). While the average total score for full colour vision participants was approximately the exact same regardless of the colour scheme, colour-blind participants who viewed the gradient-blue palette obtained a slightly higher score. The results of the Logistic Regression indicate that the blue colour scheme has a positive effect for both groups: for the full colour vision participants, the blue colour scheme is associated with an increase of around 4.8% on the odds of answering correctly Covid-19 related questions when compared to the green-red scheme, while for colour-blind participants, it is associated with an increase of approximately 134%. However, none of the coefficients or the interaction between them were significant ($p > 0.05$).

4.2 Effect on Risk Perception

The first risk perception question asked participants to rate how risky they perceived a scenario depicted by a point drawn in the risk matrix to be, on a 5-point scale (from not risky at all to very risky). The results are displayed on Figure 17.

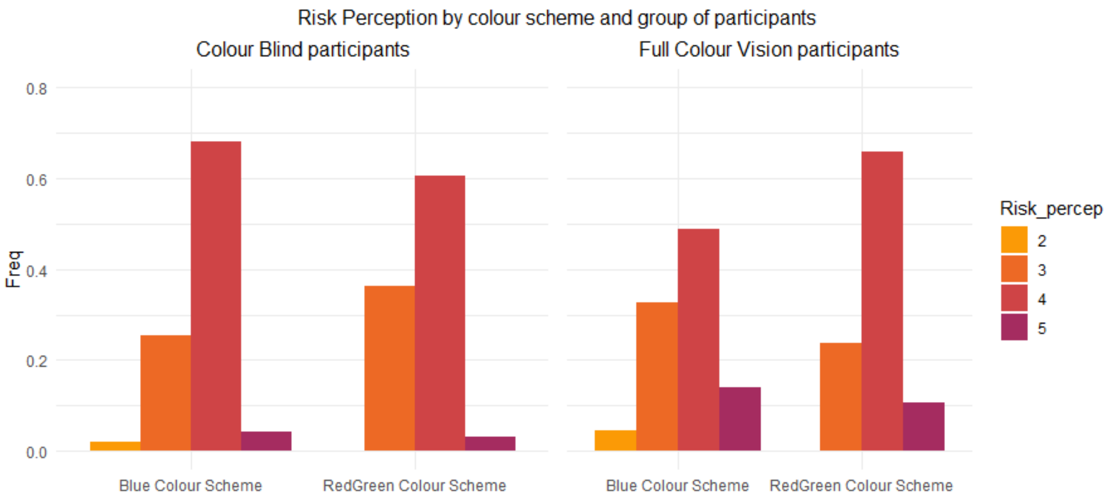

Figure 17 – Risk perception ratings, by group.

Table 9 – Ordinal regression results for risk perception rating.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
Blue	-0.047	0.461	0.9543	[0.3863;2.3574]	0.311
Colour blindness	-0.654	0.474	0.5202	[0.2054;1.3168]	0.168
Blue*Colour blindness	0.771	0.640	2.1608	[0.6162;7.5768]	0.229

Table 10 – Threshold coefficients for the risk perception ratings.

Threshold Coefficients	Estimate	SE
2|3	-4.349	0.6606
3|4	-1.1679	0.3453
4|5	2.0939	0.3939

The ordinal regression output shows that the coefficients for Blue and Colour blindness are negative, indicating that the blue colour scheme makes rating risk perception in higher categories slightly less likely for full colour vision individuals – the odds are approximately

4.57% lower -, and that colourblind individuals are less likely to rate risk perception in higher categories for the green-red colour scheme when compared to full colour vision individuals – the odds of rating in higher rather than low categories of the ordinal scale are approximately 48% lower. The interaction term is positive, indicating that for colour-blind individuals, viewing the blue colour scheme makes rating risk perception in higher categories more likely than when viewing the green-red scheme. The *p-values* associated with these coefficients are larger than 0.05, indicating that the coefficients are not statistically significant. The threshold coefficients (or intercepts) can be interpreted as the log odds of identifying in the listed categories for the reference group (full colour vision participants viewing the green-red scheme). The predicted probabilities, presented in Table 24 in the Annex, are calculated using these intercepts and the different coefficients, according to the group's conditions.

After evaluating the risk associated to a point drawn inside the risk matrix, participants were asked to evaluate their intention to adhere to Covid-19 health-related guidelines, again in a 5-point scale (from no intention at all to very strong intention). The results are displayed on Figure 18.

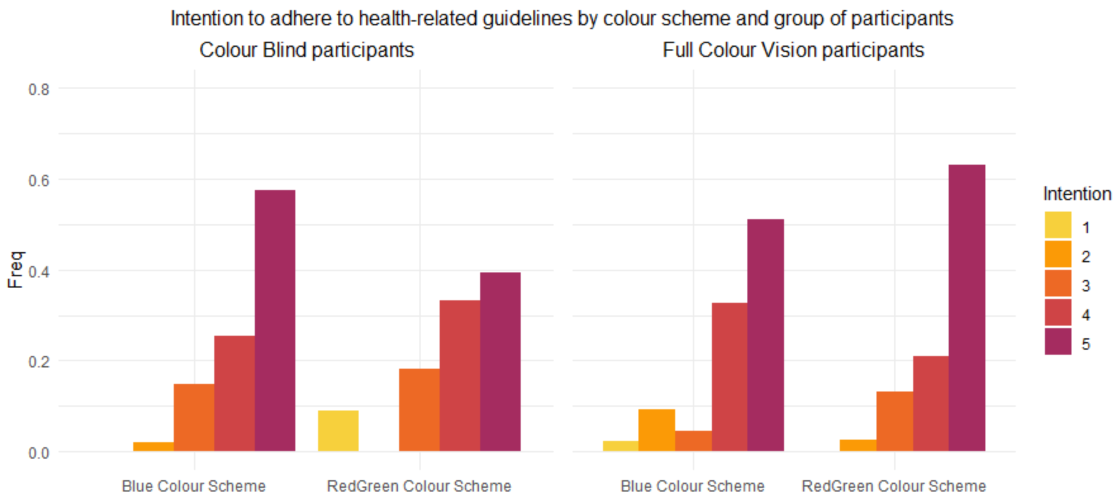

Figure 18 – Intention to adhere to health-relatedguidelines, by grup.

Table 11 – Ordinal regression results for the intention to adhere to health-related guidelines rating.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
Blue	-0.444	0.438	0.6415	[0.2719;1.5131]	0.3107
Colour blindness	-0.934	0.460	0.3931	[0.1596;0.9683]	0.0424
Blue*Colour blindness	1.171	0.613	3.2259	[0.9705;10.721]	0.0560

Table 12 – Threshold coefficients for the intention ratings.

Threshold Coefficients	Estimate	SE
1|2	-4.084	0.5911
2|3	-3.1223	0.4453
3|4	-1.8746	0.3618
4|5	-0.5107	0.3306

The results follow the same pattern of the risk perception question, but the magnitude of the effects is larger: when viewing the blue colour scheme, full colour vision participants are less likely to rate their intention to adhere to Covid-19 related guidelines in higher categories than when seeing the green-red colour scheme – the odds of rating in higher categories are around 36% lower. Colour-blind participants' odds of rating their intention in higher categories for the green-red colour scheme are 61% lower than the odds of full colour vision participants ($p < 0.05$). Lastly, viewing the blue colour scheme rather than the green one increases colourblind participants' odds of rating their intention in higher categories. The threshold coefficients, that represent the log odds of identifying in the listed categories for the reference group, were used to calculate the predicted probabilities, shown in Table 25, in the Annex.

4.3 Effect on Satisfaction and Preference

The last section was dedicated to assessing participants' satisfaction regarding the visual representations that they had just seen and their preference between the two colour schemes, applied to both representations. Starting with the satisfaction levels, the results for the choropleth map are displayed on Figure 19. Participants were asked to rate how satisfied they felt with the choropleth map they had seen, from 1 (very dissatisfied) to 5 (very satisfied).

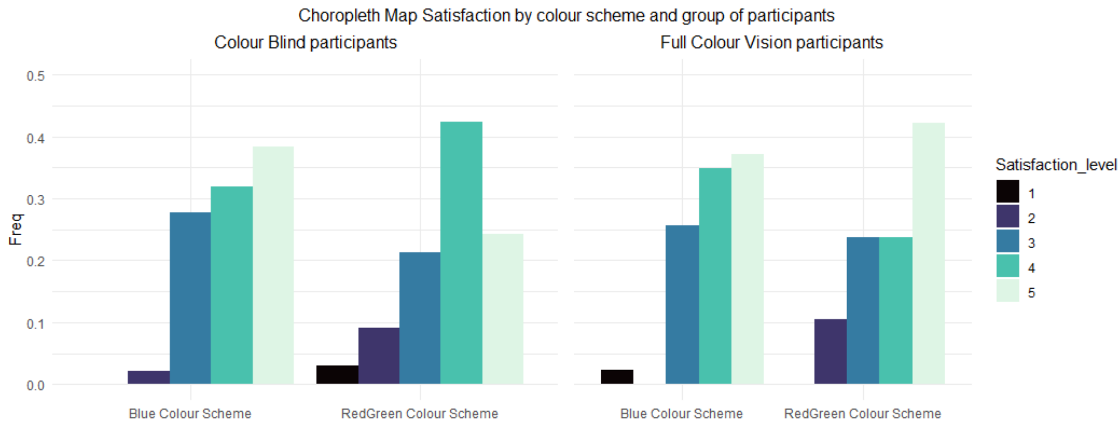

Figure 19 – Choropleth map satisfaction ratings, by group.

Table 13 – Ordinal regression results for the choropleth map satisfaction rating.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
Blue	0.078	0.415	1.0813	[0.4796;2.4377]	0.8510
Colour blindness	-0.406	0.440	0.6662	[0.2810;1.5791]	0.3560
Blue*Colour blindness	0.403	0.583	1.4968	[0.4777;4.6894]	0.4890

Table 14 – Threshold coefficients for the choropleth map satisfaction rating.

Threshold Coefficients	Estimate	SE
1|2	-4.4336	0.7614
2|3	-2.7663	0.4256
3|4	-0.8439	0.3257
4|5	0.5358	0.3195

The positive coefficient of the Blue colour scheme and of the interaction between the Blue colour scheme and being colourblind indicate that seeing the blue colour scheme increases the participants' odds of rating their satisfaction with the choropleth map in higher categories when in comparison with seeing the green-red one. In other words, the blue colour scheme increases the odds of being more satisfied with the choropleth map, both for full colour vision and colourblind individuals. However, none of the coefficients is statistically significant.

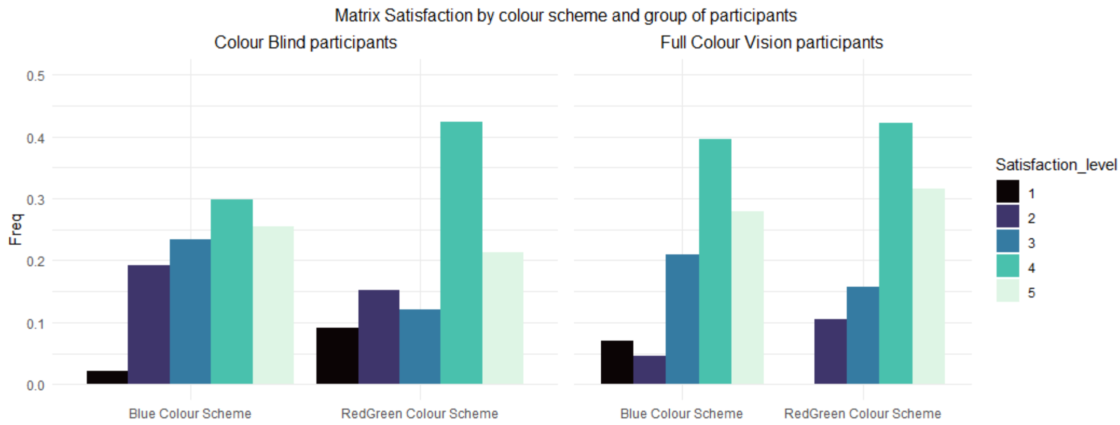

Figure 20 – Risk matrix satisfaction ratings, by group.

Table 15 – Ordinal regression results for the risk matrix satisfaction rating.

	Estimate	SE	Odds Ratio	Odds Ratio 95% CI	p-value
Blue	0.234	0.400	1.2635	[0.5768;2.7673]	0.5590
Colour blindness	-0.592	0.433	0.5530	[0.2367;1.2918]	0.1710
Blue*Colour blindness	0.240	0.576	1.2716	[0.4108;3.9355]	0.6770

Table 16 – Threshold coefficients for the risk matrix satisfaction rating.

Threshold Coefficients	Estimate	SE
1|2	-3.4721	0.4723
2|3	-1.9712	0.3395
3|4	-0.9562	0.3071
4|5	0.6743	0.303

The results of the risk matrix satisfaction ordinal regression also show that the blue colour scheme increases the participant's odds of rating their satisfaction with the risk matrix in higher categories than the green-red colour scheme, but again, the coefficients are not statistically significant.

Lastly, participants were asked to choose their preferred colour scheme, applied to the choropleth map and to the risk matrix.

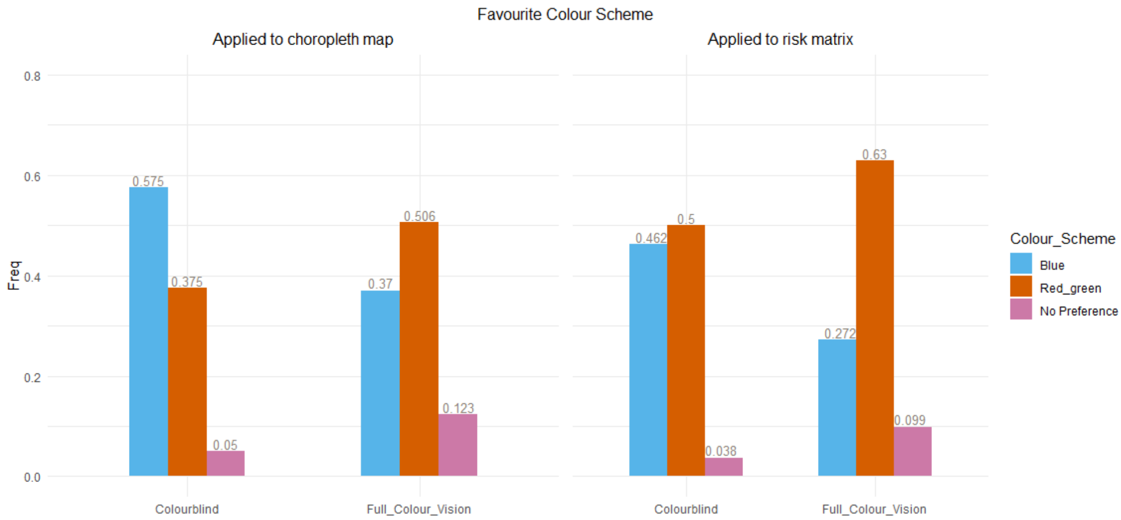

Figure 21 – Participants' favourite colour scheme, applied to the two visual representations.

Although the majority of the colourblind participants (57.5%) preferred the blue colour scheme for the choropleth map, the most preferred colour scheme for the risk matrix was the green-red one (50%). For the full colour vision participants, the green-red colour scheme was the preferred in both visual representations, with 50.6% of the participants electing it as its favourite when applied to the choropleth map and 63% when applied to the risk matrix.

5. Conclusion

5.1 Main findings

The present work aimed to, firstly, evaluate the efficiency of the graphical visualisations employed to communicate the risk associated with the Covid-19 pandemic for individuals with colour-blindness and, secondly, assess whether an alternative colour scheme to the typically used green-red one improves colour-blind individuals' comprehension of these visualizations without damaging the interpretation of full colour vision individuals. For that matter, different colour schemes applied to two types of graphical visualizations were evaluated on two groups: full colour vision and colour-blind individuals.

The experiment analysis showed that participants had an overall good understanding of both visual representations, regardless of the group they were assigned to. All the accuracy questions had an approval rate of at least 85%, and the lowest score obtained by a group was fixed at 74.4% of proportion of right answers. Therefore, there is no evidence against the use of these two types of graphical representations for depicting Covid-19 related information, as both the choropleth map and the risk matrix delivered very positive results in this experiment, in regards to interpretation of the displayed information.

When it comes to comparing the results between different groups, the experiment did not produce significant results for the effect that the different vision types and the different colours have on the target variables of the study, which included accuracy of interpretation, risk perception and satisfaction of the subjects. Therefore, there is no evidence to choose a certain colour-scheme over the other, or to state that one of them produces better results in terms of user's comprehension. Nonetheless, non-significant results are also results, and these showed that, for all the evaluated metrics, the interaction between being colour-blind and seeing the gradient-blue colour scheme was positive. For three out of the four interpretation questions, the blue colour scheme increased the probability of colour-blind individuals correctly understanding the displayed information. This alternative colour scheme also increased the probability of colour-blind individuals rating their risk perception and their intention to engage in protective behaviour in higher levels than when seeing the green-red one and, in terms of satisfaction with the displayed graphics, the blue-gradient palette led to higher satisfaction ratings in both groups – full colour vision and colour-blind individuals. For full colour vision participants, the blue palette practically did not impact the total obtained score, but it did negatively influence the probability of rating risk perception and intention to engage in protective behaviour in higher categories – which is not a surprise, as the literature has often pointed out that colours such as red, yellow and orange have been shown to increase hazard ratings.

Regarding the favourite colour scheme applied to the choropleth map, the majority of colour-blind participants chose the blue one. The same, however, did not happen for the risk matrix, for which the most preferred colour scheme was the green-red one. This might be related to the fact that the risk matrix has two axes, that serve as extra visual clues for correctly interpreting the visualization, which makes it possible for colour-blind people to not rely solely on the colour encoding that the graphic uses, unlike what happens with choropleth map. Full colour vision individuals elected the green-red one as their favourite for both graphical representations, which once again is in accordance with what previous studies have pointed out: because of most people's familiarity with green-red colour schemes, these are their most preferred ones for displaying risk information.

Because these reported effects were not statistically significant, one cannot say for sure that the results obtained in this experiment are not actually null. That is why proceeding with research in this field, and eliminating some of the limitations that were present in this work that will be explored in the next section, would be an important step for a better understanding of how can we make information visualization more accessible for everyone.

5.2 Limitations and Future Work

As in any other research work, there were certain limitations in this piece that might have affected its final conclusions. This section will provide an outline of these shortcomings, finally concluding with what are some of the key aspects future researchers should aim for in studies to come.

One of the limitations of this work consisted on the sample size. Although a previous estimation of the adequate sample size was carried out, due to the fact that all participants were monetarily rewarded and that this is an academic work, there was a limit to the number of participants this study could recruit. Larger samples provide more reliable results, and it is something future researchers should have in account if conducting a similar study. Having used a small sample might partially explain having obtained mostly non-significant results.

Besides the sample size, the collected sample may not be sufficiently representative. Graph interpretation depends not only on the features of the graph that is being displayed, but also on the viewers' previous knowledge of the subject, reasoning skills, among others. These variables are not easy to control, and some of them might have impacted the final results. Two of them, that are worth pointing out, are the fact that more than half of the participants had completed higher education degrees and had an age average of 28 years. Future studies should collect data from people of different ages and more diverse educational backgrounds.

It should also be mentioned that, because data collection was made using online-based surveys, there is no way to guarantee that participants answered the questions based on their own knowledge and without any external help. An interesting step forward in the future would be to perform these studies in person, as it would also facilitate collecting data regarding the average time response of each user and to have one more variable to investigate. The analysis of this variable was not included in this study as, once again, because web-based surveys were used, the reliability of this metric would be compromised.

Finally, the lack of previous research studies on this topic is also a limitation worth mentioning. Although there is quite some literature on the use of colour for risk visualization, prior studies on risk visualization of infectious disease were limited. The same happens for guidelines on how to build colour-blind safe visualizations. Although some recommendations have been put forward, there are not many studies that actually evaluate the efficiency of these suggestions. As prior studies provide theoretical foundations for the research in question, having limited resources to build upon can also be identified as one limitation of this work. Nonetheless, it actually reinforces the relevance of this research and, as was mentioned in the beginning of this piece, this work precisely aimed to fill in this gap on risk visualization research and, hopefully, will be of use for future research in this field.

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Annex

Effectiveness and Accessibility of COVID-19 Visual Representations

Introduction and context: The present study is part of a master's Thesis in Data Analytics, which is being developed at the School of Economics and Management of the University of Porto.

Objectives of the study: The objective of this study is to assess if certain visual representations of data for depicting the risk associated to the Covid-19 Pandemic are effective, inclusive and accessible for their broad audience, with focus on their color palette. With this work, the researchers aim to gain new knowledge on how to improve risk communication for people with colour-vision deficiency, without damaging the interpretation of full coloured vision users.

Procedures: Participation in this study involves answering questions relating to color interpretation, graph comprehension, risk perception, intention to adhere to infection control guidelines and overall satisfaction.

Eligibility: To be eligible for taking part in this study, the participant needs to fulfill all the following requirements:

- Experiencing some kind of colour blindness;
- Be at least 18 years old;
- Have a good command of English language;
- Not reside in Portugal.

Risks and benefits: There are no risks associated with participation in this study. All participants will be paid for completing this study, according to Prolific's pricing policy.

Voluntary participation: Participation in this study is completely voluntary.

Confidentiality and Data Protection: The questionnaire is implemented on Jotform. All answers will be downloaded from the platform to the researcher's computer where they will be analysed in aggregate form, i.e. together with the answers given by all the people responding to the study. Each participant will only be identified to the researcher with an alphanumeric code assigned automatically and randomly by the questionnaire platform. Furthermore, the researcher undertakes to treat all information confidentially.

Purpose of data processing and dissemination of results: The collection and processing of data are carried out, exclusively, for scientific research purposes. The final results of the study may be published in scientific journals and academic journals, presented in seminars, conferences, lectures or other activities with academic purposes, in which the results will only be mentioned in aggregate form. Participant's data will not be processed for purposes other than those previously indicated. The statistical treatment database may eventually be required by the scientific journal for the publication of the results. In such cases, the statistical treatment database will have to be shared with free access, and it will not be possible in any case to identify the participants.

By advancing you are indicating that you have read and understood the information above; that you fulfill all the previously mentioned requirements and are eligible to participate; that you commit to thoughtfully provide your best answers to each question in this Survey and that you freely agree to participate in this study. By advancing you are also authorizing the collection, processing and storage of the personal data identified above for the purpose for which they are intended, and indicating that you agree with the method of dissemination of the results.

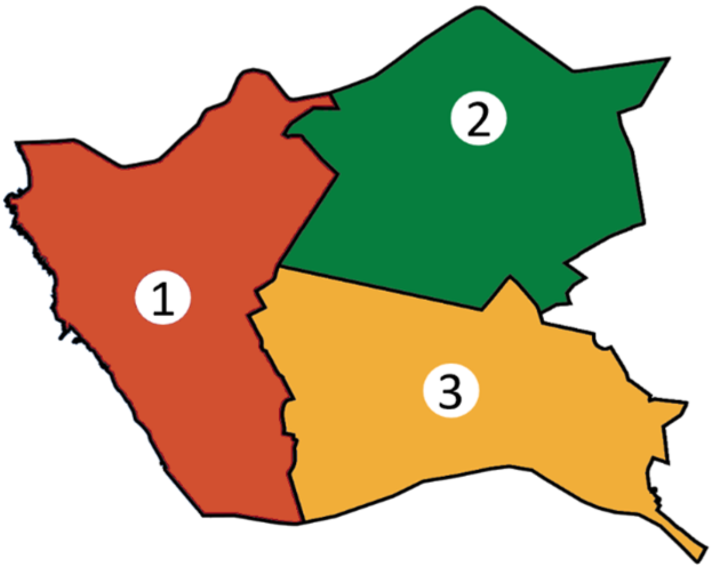
I carefully read the information provided and am eligible to participate in this study.

Figure 22 – Survey first introductory page.

As was mentioned in the previous section, this study aims to assess the effectiveness of visual representations of data for depicting the risk associated to the Covid-19 Pandemic.
Because these visual representations rely on the use of color to encode different levels of hazard, you will be asked to compare different colors in terms of the level of hazard you think they depict.
Afterwards, you will see a graphical representation called Risk Matrix, that displays the Transmissibility Rate (on the horizontal axis) and the Number of New cases in the last 14 days by 100 000 inhabitants (on the vertical axis), and will be asked some questions related to this graphical representation.
Please answer the questions as quickly as possible, without thinking too much.

Figure 23 – Survey second introductory page.

Imagine three different cities that are currently under different hazard levels in what concerns the COVID-19 Pandemic.
Their hazard levels are encoded with the colors displayed below.



Which of the cities do you think is in a riskier situation? *

- City 1
- City 2
- City 3
- It's hard to say / I don't know.

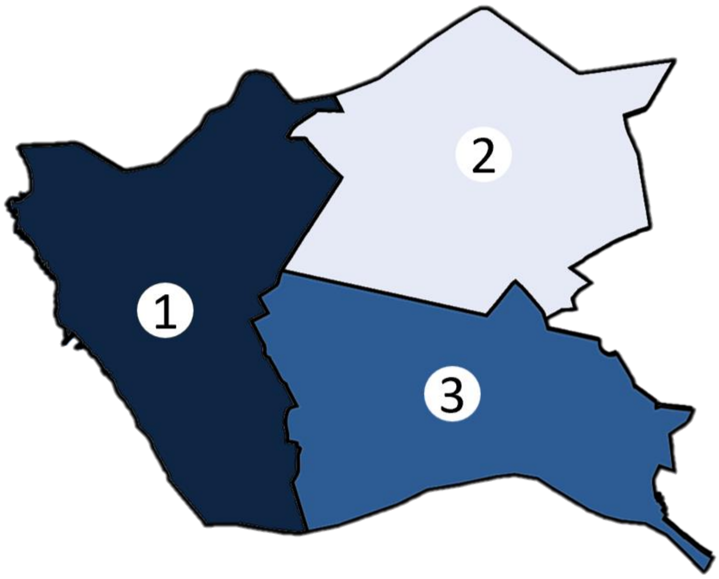
On the other hand, which of the cities do you consider to be in the safest situation? *

- City 1
- City 2
- City 3
- It's hard to say / I don't know.

Next

Figure 24 – Choropleth map interpretation questions for the green-red colour-scheme.

Imagine three different cities that are currently under different hazard levels in what concerns the COVID-19 Pandemic.
Their hazard levels are encoded with the colors displayed below.



Which of the cities do you think is in a riskier situation? *

- City 1
- City 2
- City 3
- It's hard to say / I don't know.

On the other hand, which of the cities do you consider to be in the safest situation? *

- City 1
- City 2
- City 3
- It's hard to say / I don't know.

Next

Figure 25 – Choropleth map interpretation questions for the gradient blue colour-scheme.

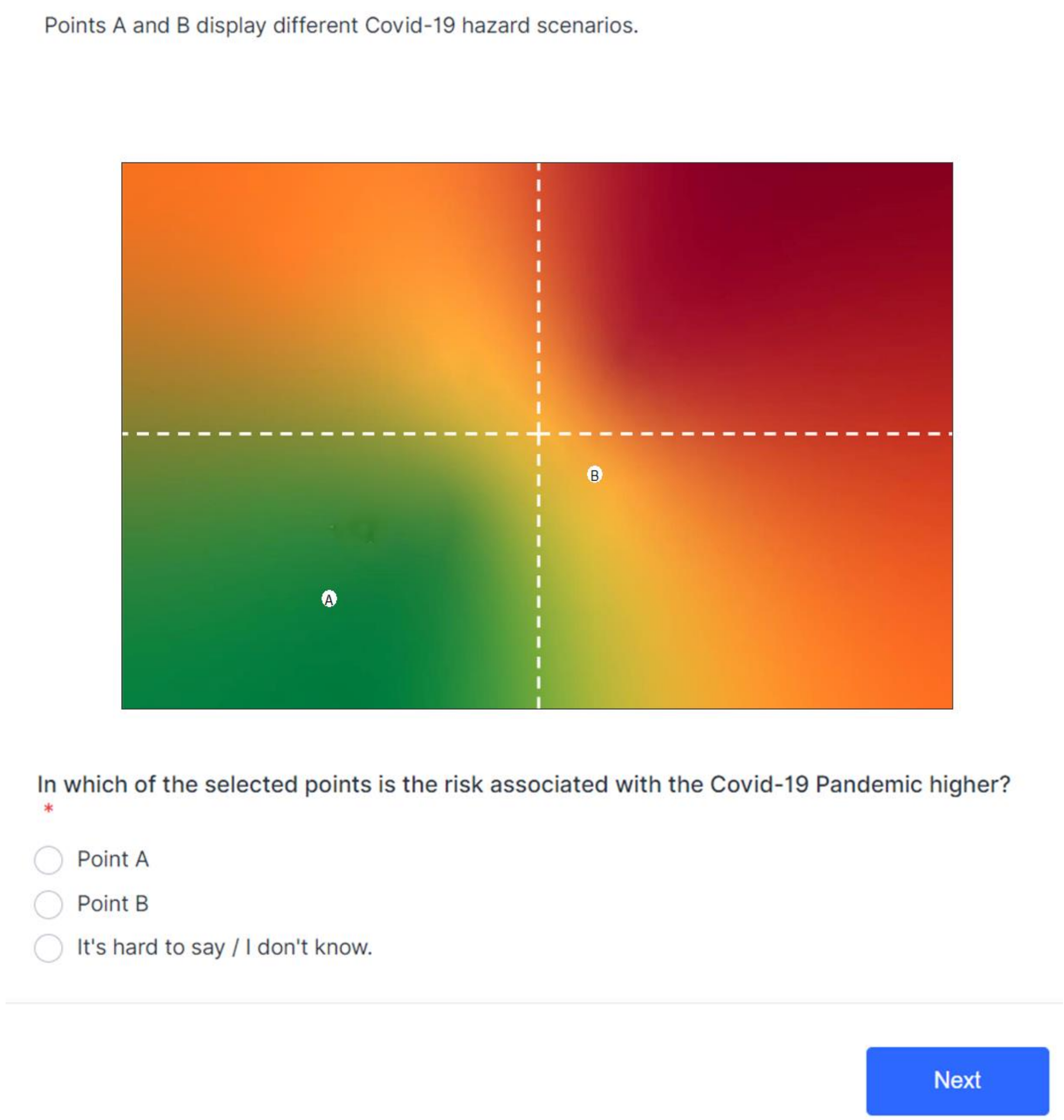
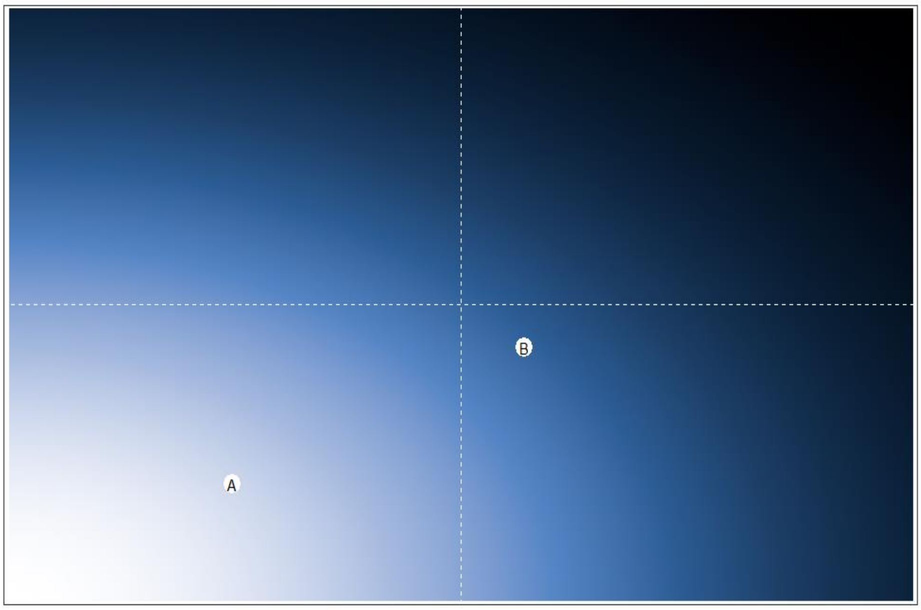


Figure 26 – First risk matrix interpretation question for the green-red colour scheme.

Points A and B display different Covid-19 hazard scenarios.

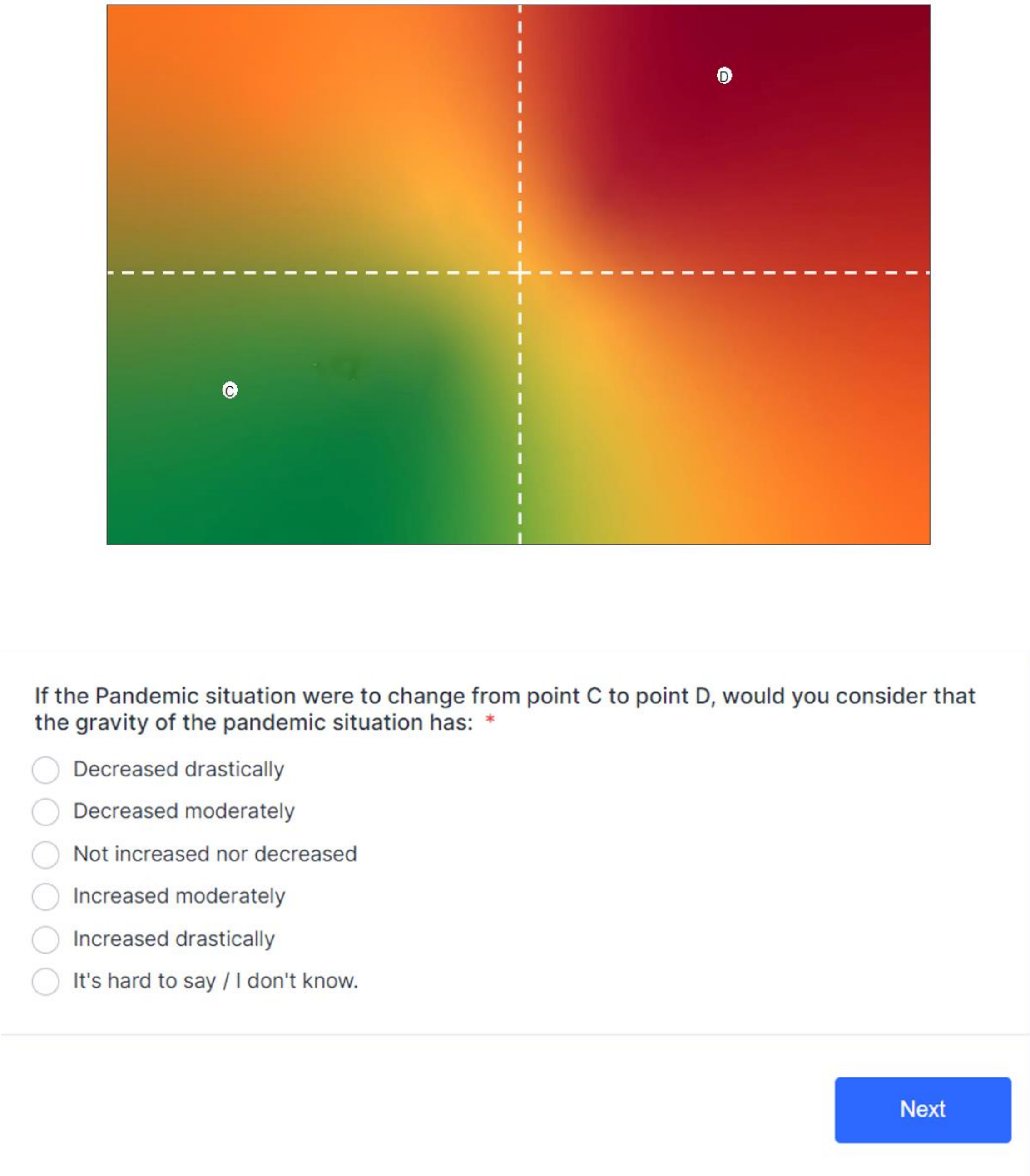


In which of the selected points is the risk associated with the Covid-19 Pandemic higher?
*

- Point A
- Point B
- It's hard to say / I don't know.

Next

Figure 27 – First risk matrix interpretation question for the blue-gradient colour scheme.

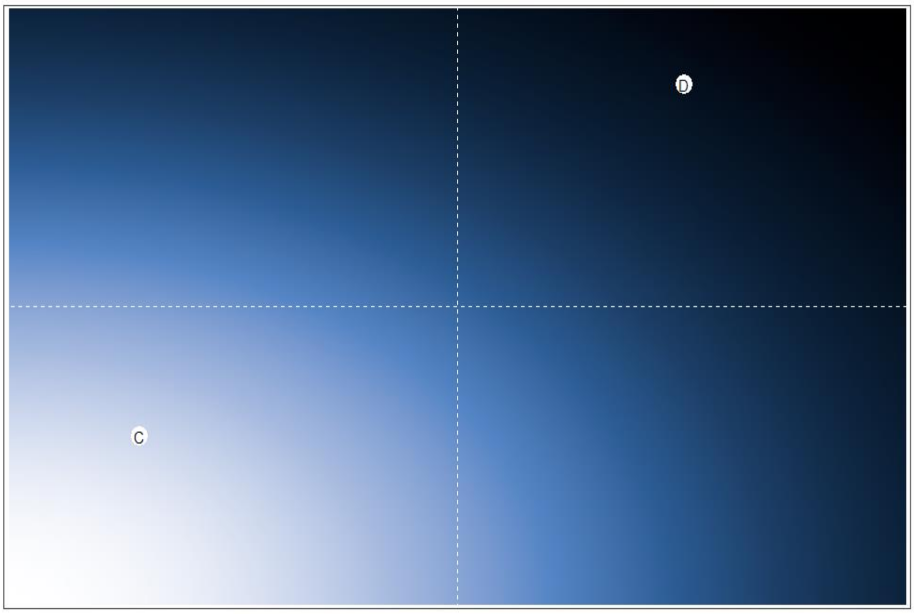


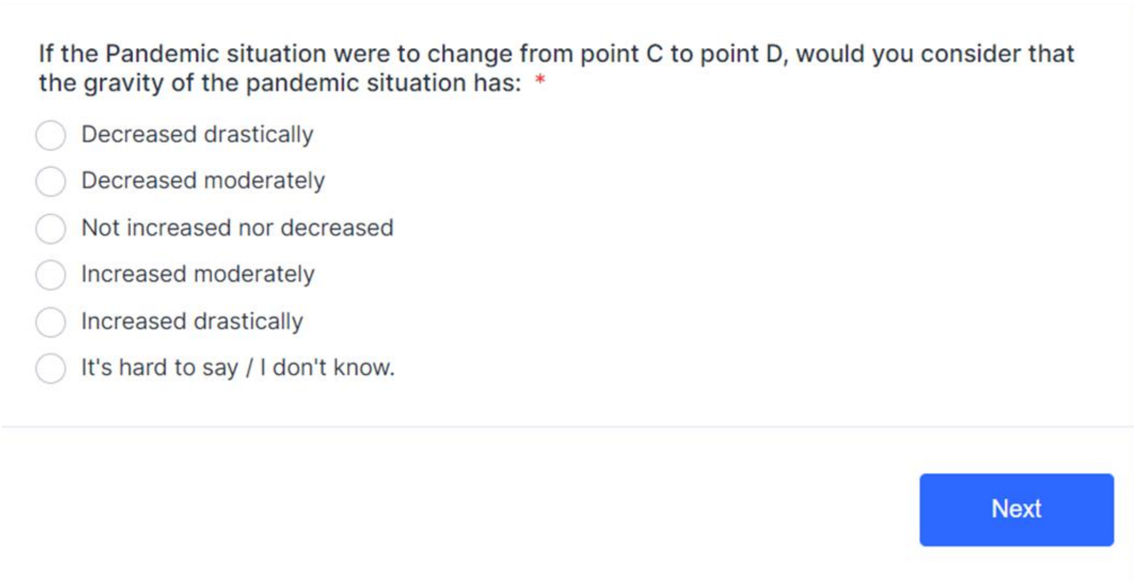
If the Pandemic situation were to change from point C to point D, would you consider that the gravity of the pandemic situation has: *

- Decreased drastically
- Decreased moderately
- Not increased nor decreased
- Increased moderately
- Increased drastically
- It's hard to say / I don't know.

Next

Figure 28 – Second risk matrix interpretation question for the green-red colour scheme.

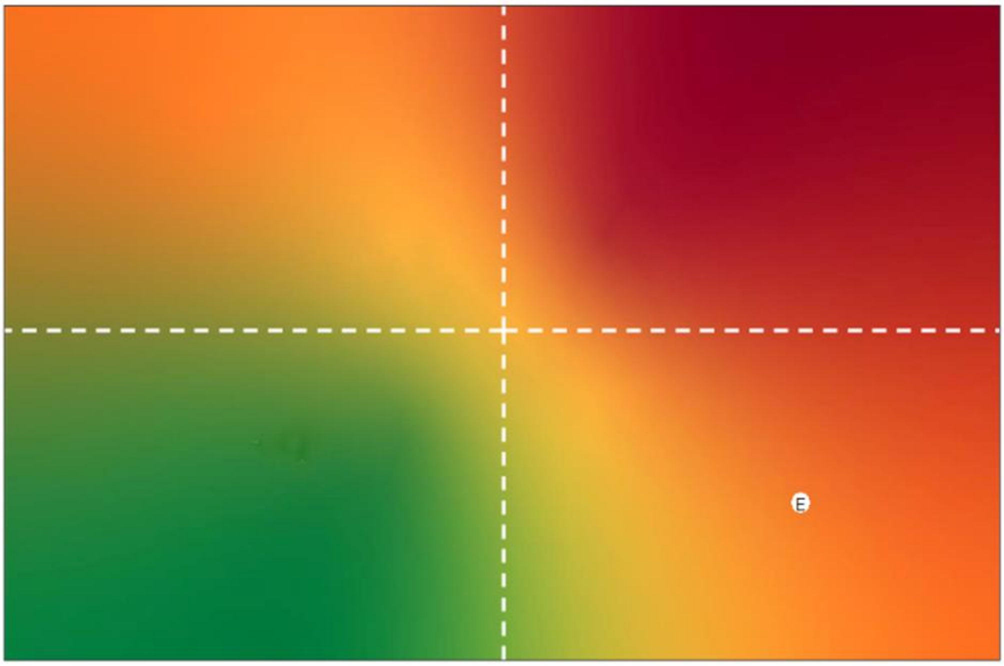



If the Pandemic situation were to change from point C to point D, would you consider that the gravity of the pandemic situation has: *

- Decreased drastically
- Decreased moderately
- Not increased nor decreased
- Increased moderately
- Increased drastically
- It's hard to say / I don't know.

Next

Figure 29 – Second risk matrix interpretation question for the gradient blue colour scheme.



Imagine that the pandemic situation in the country where you live is represented by point E, and please answer the following questions:

On a scale from 1 (not risky at all) to 5 (very risky), how risky would you perceive the pandemic situation to be? *

1 2 3 4 5

Not risky at all — Very risky

On a scale from 1 (no intention at all) to 5 (very strong intention), how strong would your intention be to adhere to Covid-19 health-related guidelines? *

1 2 3 4 5

No intention at all — Very strong intention

Next

Figure 30 – Risk perception and intention to engage in protective behaviour questions for the green-red colour scheme.

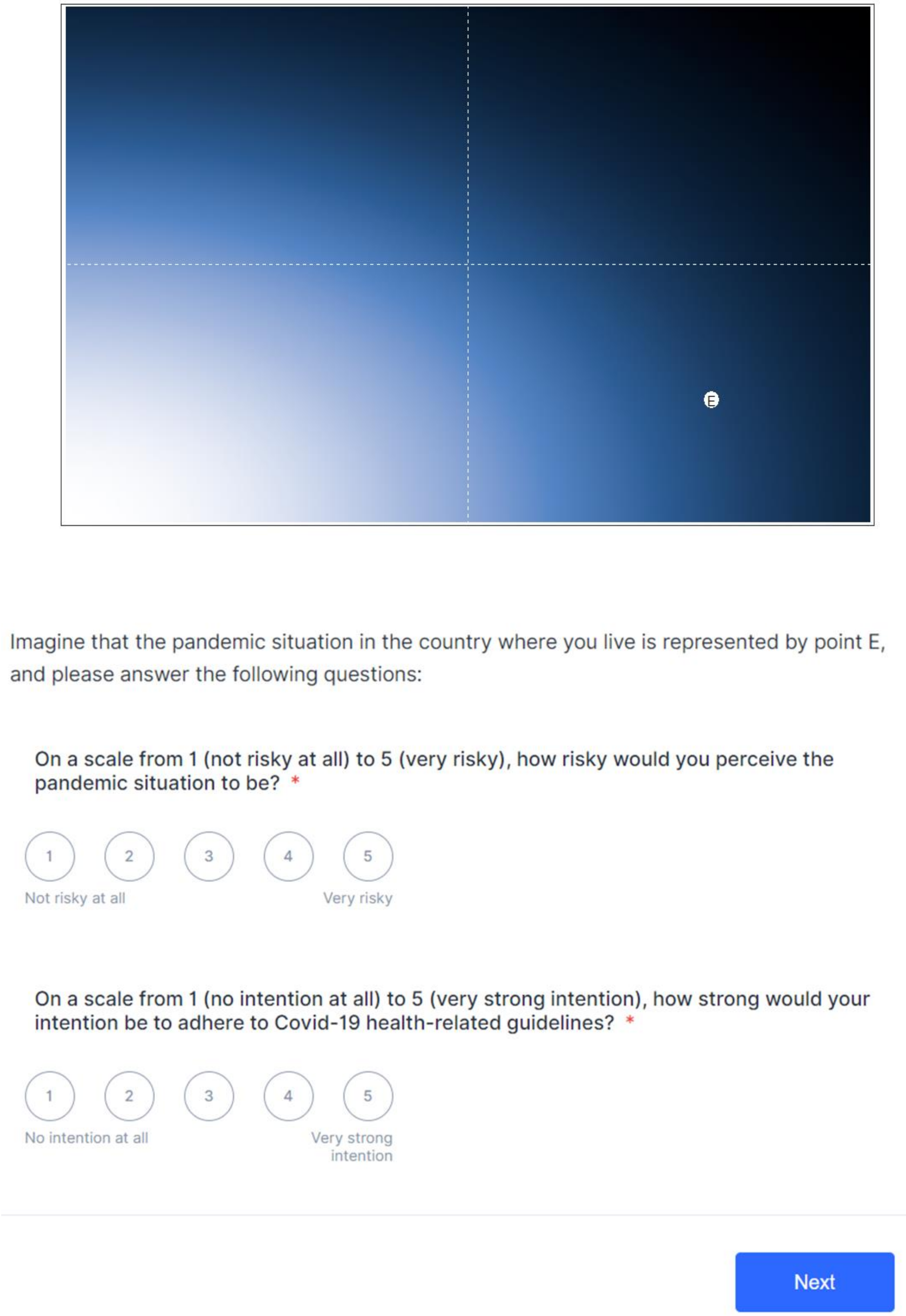
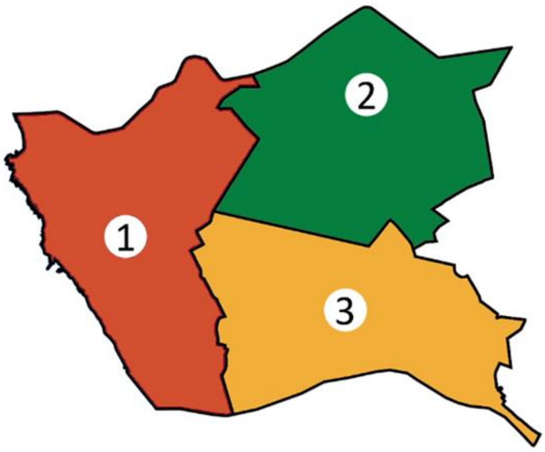


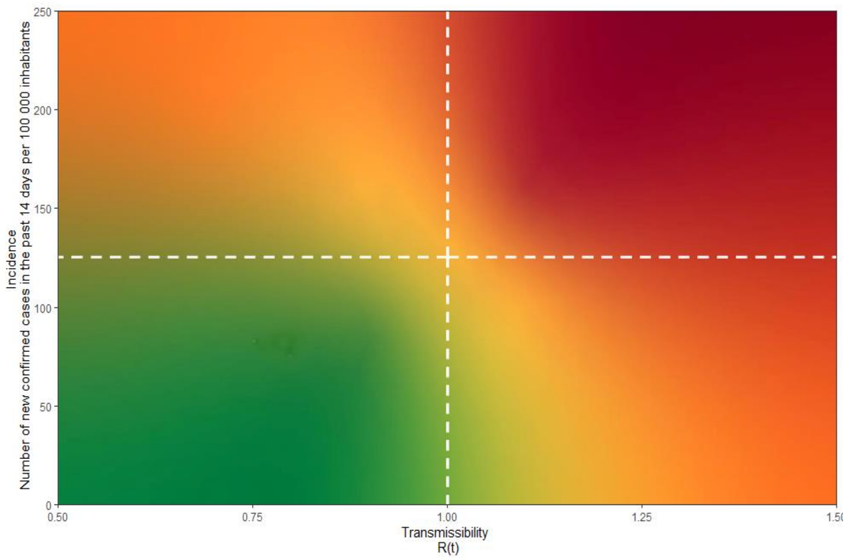
Figure 31 – Risk perception and intention to engage in protective behaviour questions for the blue-gradient colour scheme.



How satisfied do you feel with the map that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic of multiple cities? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied). *

1 2 3 4 5

Very dissatisfied Very satisfied

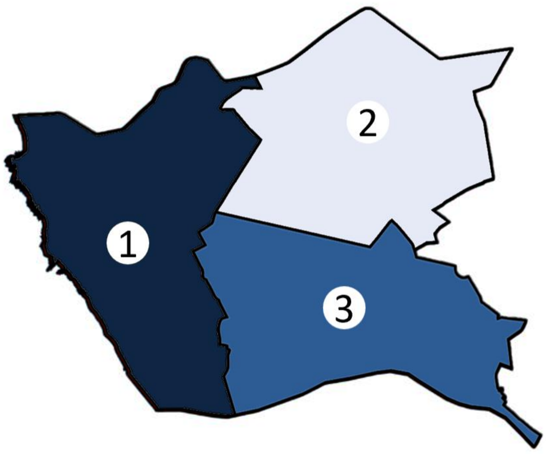


How satisfied do you feel with the risk matrix that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied). *

1 2 3 4 5

Very dissatisfied Very satisfied

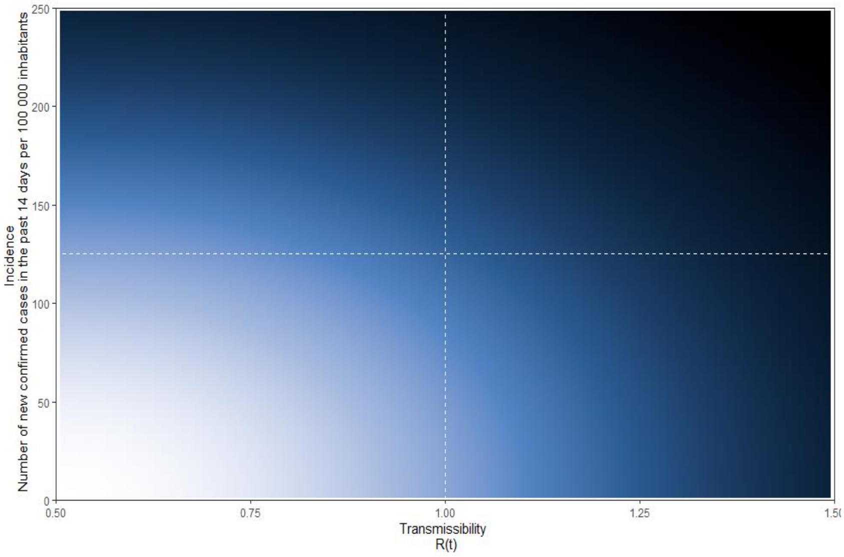
Figure 32 – Choropleth map and risk matrix satisfaction questions for the green-red colour scheme.



How satisfied do you feel with the map that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic of multiple cities? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied). *

1 2 3 4 5

Very dissatisfied Very satisfied

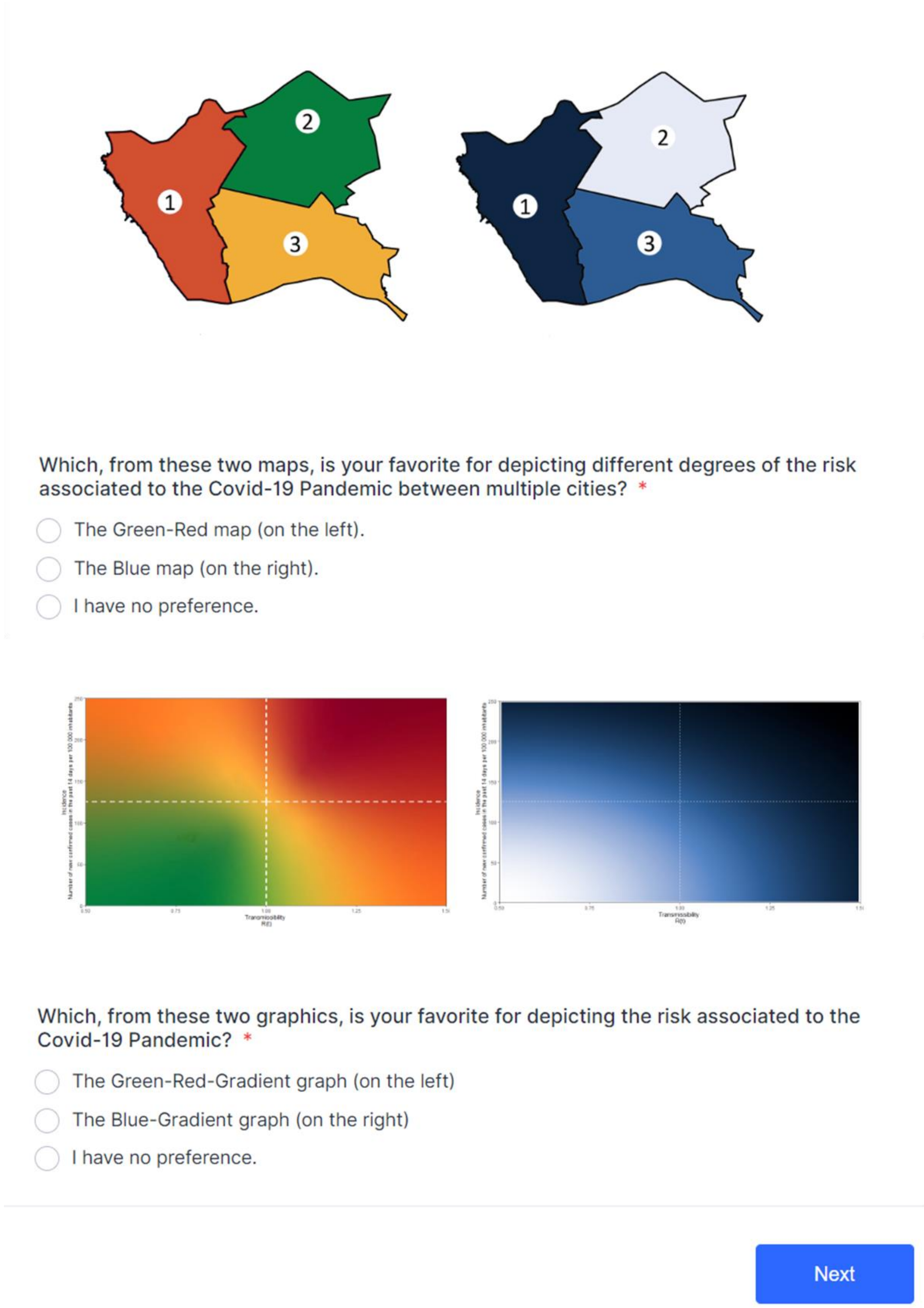


How satisfied do you feel with the risk matrix that has been shown in this experiment, given its purpose of depicting the risk associated to the Covid-19 Pandemic? Please choose your score from 1 (very dissatisfied) to 5 (very satisfied). *

1 2 3 4 5

Very dissatisfied Very satisfied

Figure 33 – Choropleth map and risk matrix satisfaction questions for the blue-gradient colour scheme.



Which, from these two maps, is your favorite for depicting different degrees of the risk associated to the Covid-19 Pandemic between multiple cities? *

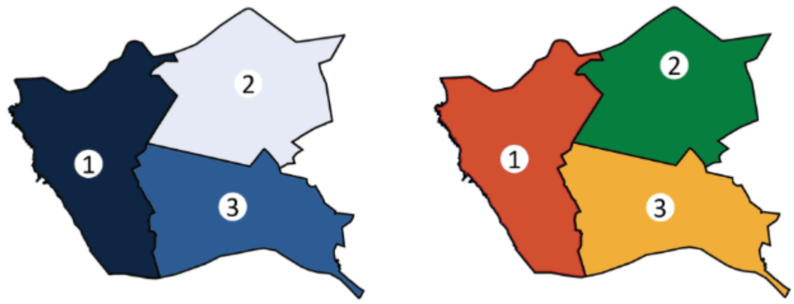
- The Green-Red map (on the left).
- The Blue map (on the right).
- I have no preference.

Which, from these two graphics, is your favorite for depicting the risk associated to the Covid-19 Pandemic? *

- The Green-Red-Gradient graph (on the left)
- The Blue-Gradient graph (on the right)
- I have no preference.

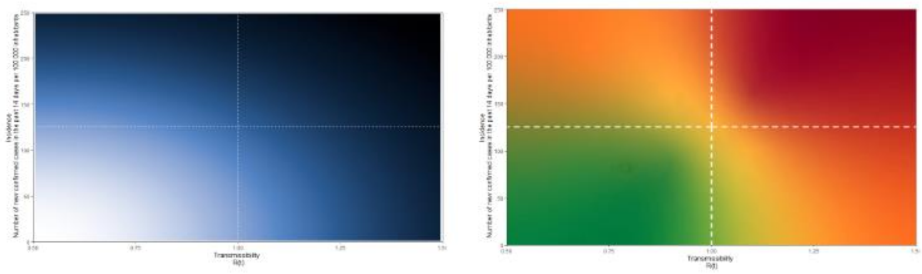
Next

Figure 34 – Favourite colour scheme questions for viewers of the green-red colour scheme.



Which, from these two maps, is your favorite for depicting different degrees of the risk associated to the Covid-19 Pandemic between multiple cities? *

- ◯ The Blue map (on the left).
- ◯ The Green-Red map (on the right).
- ◯ I have no preference.

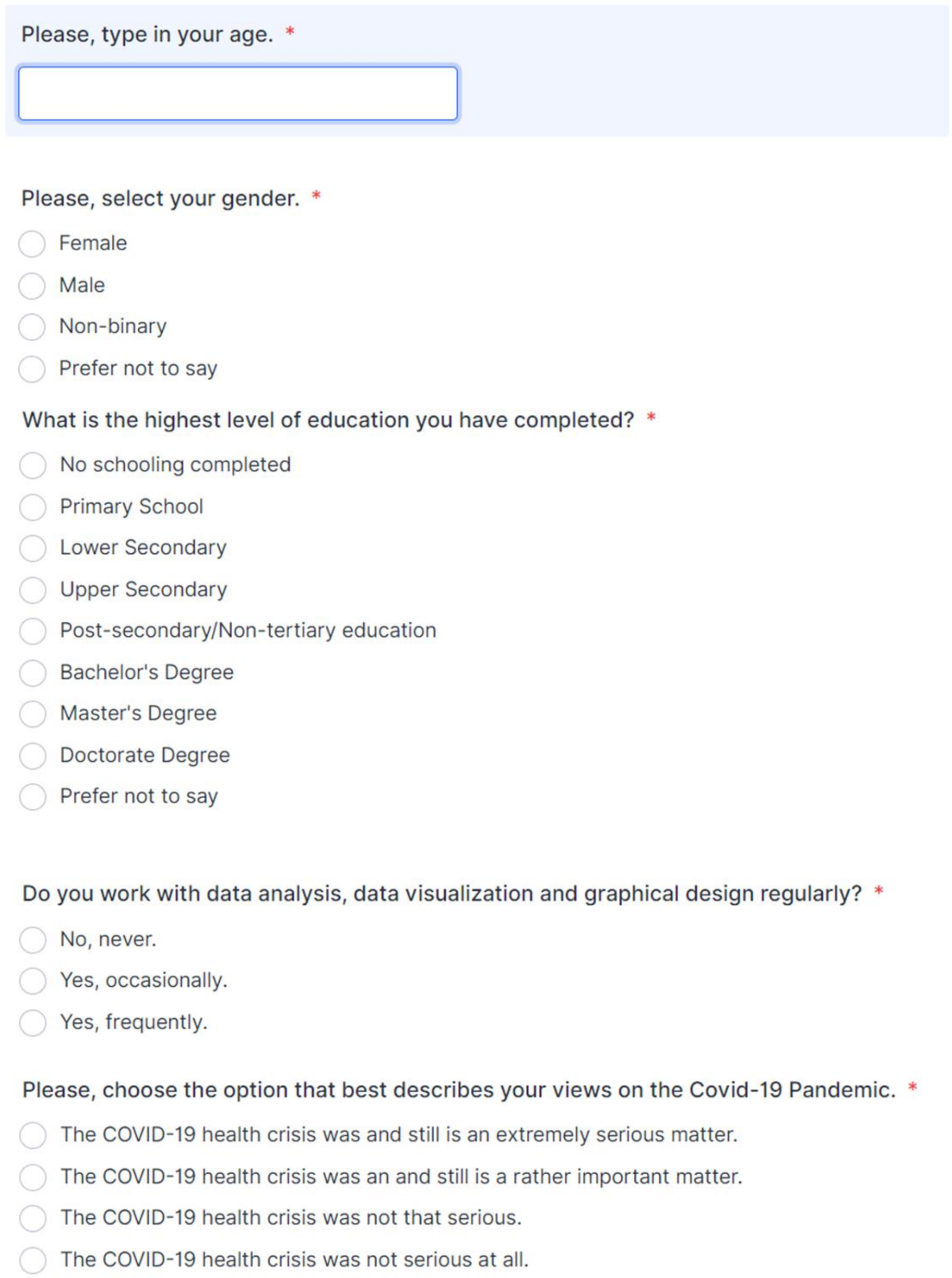


Which, from these two graphics, is your favorite for depicting the risk associated to the Covid-19 Pandemic? *

- ◯ The Blue-Gradient graph (on the left).
- ◯ The Green-Red-Gradient graph (on the right).
- ◯ I have no preference.

Next

Figure 35 – Favourite colour scheme questions for viewers of the gradient-blue colour scheme.


Please, type in your age. *

Please, select your gender. *

- Female
- Male
- Non-binary
- Prefer not to say

What is the highest level of education you have completed? *

- No schooling completed
- Primary School
- Lower Secondary
- Upper Secondary
- Post-secondary/Non-tertiary education
- Bachelor's Degree
- Master's Degree
- Doctorate Degree
- Prefer not to say

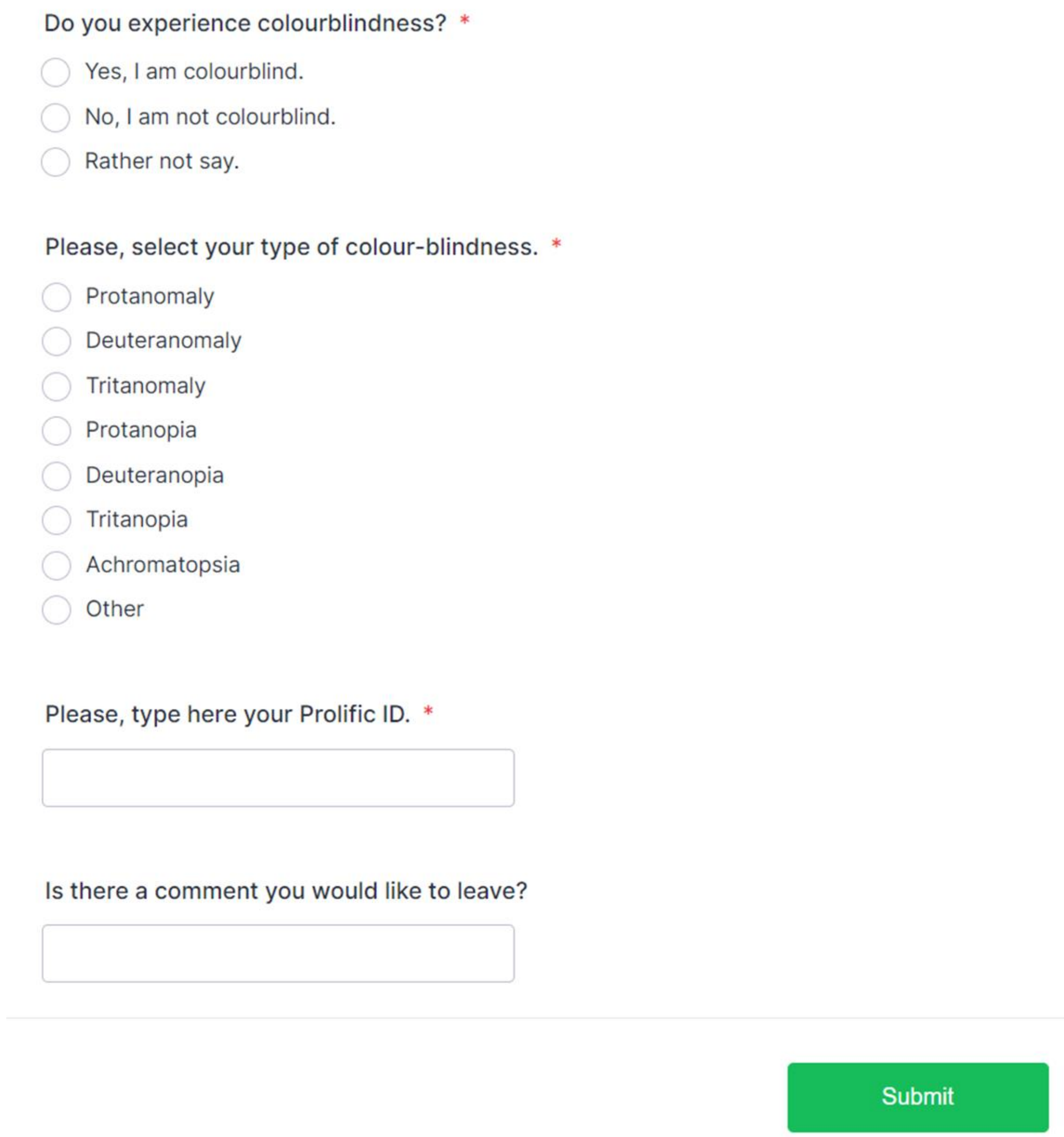
Do you work with data analysis, data visualization and graphical design regularly? *

- No, never.
- Yes, occasionally.
- Yes, frequently.

Please, choose the option that best describes your views on the Covid-19 Pandemic. *

- The COVID-19 health crisis was and still is an extremely serious matter.
- The COVID-19 health crisis was an and still is a rather important matter.
- The COVID-19 health crisis was not that serious.
- The COVID-19 health crisis was not serious at all.

Figure 36 – First part of the demographic and sample characterization questions.


Do you experience colourblindness? *

- Yes, I am colourblind.
- No, I am not colourblind.
- Rather not say.

Please, select your type of colour-blindness. *

- Protanomaly
- Deuteranomaly
- Tritanomaly
- Protanopia
- Deuteranopia
- Tritanopia
- Achromatopsia
- Other

Please, type here your Prolific ID. *

Is there a comment you would like to leave?

Submit

Figure 37 – Second part of the demographic and sample characterization questions and end of the survey.

Table 17 – Hexadecimal codes and HCL decomposition of the green-red palette.

Hexadecimal Code	***Hue***	***Chroma***	***Luminance***
#0D7F3D	136.251176	56.28885	46.44544
#3D8B37	126.325638	60.47463	51.53305
#66A43C	117.328360	67.34571	61.39540
#8FAD38	102.127961	67.59047	66.52925
#BFB53E	80.267920	69.94301	72.54378
#F4B038	51.719800	89.63705	76.42006
#FA9631	37.414916	102.71281	71.12107
#F77627	26.628655	118.62616	64.06636
#E85624	19.683736	126.26367	56.03183
#CC412A	16.097006	114.39814	47.99335
#AC1D28	10.500714	105.42848	37.49103
#930624	8.037808	92.18179	30.55114

Table 18 – Hexadecimal codes and HCL decomposition of the gradient-blue palette.

Hexadecimal Code	***Hue***	***Chroma***	***Luminance***
#FFFFFF	146.356	0.0000241	100.00000387
#A6BADF	249.7676	34.94596	75.17120409
#5585C5	249.7825	63.18411	54.79906622
#2C5C94	250.1333	54.02354	38.42270465
#1C3E66	250.1675	35.9871	25.71626537
#102946	250.0647	22.74982	16.19545729
#081B30	249.3144	12.98126	9.39138184
#041121	249.3614	6.745122	4.84581476
#020813	249.7163	2.872386	2.10979122
#010206	256.2976	0.7891861	0.56919437
#000001	265.8727	0.0800692	0.01978857
#000000	180	0.000000	0.000000

Table 19 – Predicted probabilities of correctly answering Q1, by group.

		Vision type	
		Full Colour Vision	Colour-blind
Colour Scheme	Green-Red	97,37%	96,97%
	Gradient-Blue	95,35%	95,74%

Table 20 – Predicted probabilities of correctly answering Q2, by group.

		Vision type	
		Full Colour Vision	Colour-blind
Colour Scheme	Green-Red	86,84%	75,76%
	Gradient-Blue	95,53%	91,49%

Table 21 – Predicted probabilities of correctly answering Q3, by group.

		Vision type	
		Full Colour Vision	Colour-blind
Colour Scheme	Green-Red	92,11%	87,88%
	Gradient-Blue	88,39%	93,63%

Table 22 – Predicted probabilities of correctly answering Q4, by group.

		Vision type	
		Full Colour Vision	Colour-blind
Colour Scheme	Green-Red	76,32%	93,94%
	Gradient-Blue	74,42%	97,87%

Table 23 – Predicted probabilities of correctly answering interpretation questions, by group.

		Vision type	
		Full Colour Vision	Colour-blind
Colour Scheme	Green-Red	88,16%	88,37%
	Gradient-Blue	88,64%	94,68%

Table 24 – Risk perception response probabilities, by group.

Vision Type	**Colour Scheme**	1	2	3	4	5
Full Colour Vision	Green-red	0%	1,28%	22,45%	65,31%	10,97%
	Gradient-blue	0%	1,34%	23,34%	64,90%	10,52%
Colour-blind	Green-red	0%	2,42%	35,00%	56,56%	6,02%
	Gradient-blue	0%	1,19%	21,29%	68,85%	11,67%

Table 25 – Intention to adhere to Covid-19 related guidelines response probabilities, by group.

Vision Type	Colour Scheme	1	2	3	4	5
Full Colour Vision	Green-red	1,66%	2,56%	9,08%	24,20%	62,50%
	Gradient-blue	2,56%	3,87%	12,87%	29,03%	51,67%
Colour-blind	Green-red	4,11%	5,97%	17,99%	32,35%	39,58%
	Gradient-blue	2,03%	3,11%	10,73%	26,58%	57,55%

Table 26 – Choropleth map satisfaction response probabilities, by group.

Vision Type	Colour Scheme	1	2	3	4	5
Full Colour Vision	Green-red	1,17%	4,74%	24,15%	33,01%	36,92%
	Gradient-blue	1,09%	4,41%	22,96%	32,79%	38,75%
Colour-blind	Green-red	1,75%	6,88%	30,60%	32,72%	28,05%
	Gradient-blue	1,09%	4,42%	23,00%	32,80%	38,69%

Table 27 – Risk matrix satisfaction response probabilities, by group.

Vision Type	Colour Scheme	1	2	3	4	5
Full Colour Vision	Green-red	3,01%	9,21%	15,54%	38,48%	33,75%
	Gradient-blue	2,40%	7,53%	13,39%	37,51%	39,16%
Colour-blind	Green-red	5,32%	14,80%	20,88%	37,01%	21,98%
	Gradient-blue	3,38%	10,18%	16,64%	38,64%	31,16%