Analysing the impact of natural metaphors in visualising COVID 19 data

Master's Thesis in the Study Program "Geoinformatics and Spatial Data Science (M.Sc.)"

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Abstract

The COVID-19 pandemic has prompted a significant increase in data visualisations. Using visual metaphors in data visualisation are increasingly used in research to enhance communication and understanding, especially when dealing with complex spatial data. Metaphors can objectively represent information and help users detect information, recognize meaningful patterns, infer conclusions, and make judgments. This study aims to explore the impacts of incorporating metaphors in the visualisation of epidemiological data, particularly in the context of diseases like COVID-19. However, it is essential to acknowledge that visual metaphors may imply conflicting attributes arising from their original concepts, potentially influencing users' interpretations adversely. Consequently, we will assess users' ability to navigate these natural metaphors, considering their distinctive features, in conjunction with exposure to standard visualisations. This research suggests that using natural metaphors that have been parameterised to mirror real world phenomena in representing COVID-19 might be difficult to process but the information understanding is similar to that of standard visualisation techniques.

Keywords: COVID-19, epidemiological visualisations, visual metaphors, glyph-based visualisation, weather metaphors, pandemic visualisations.

1.Introduction:

The most effective way to analyse and comprehend data related to pandemic diseases is through information visualisation. This makes it simple to spot trends and important areas that need more research. Empirical studies have demonstrated the value of visual aids in supporting the general public, who frequently struggle with comprehending intricate crisis dynamics, making sense of crisis scenarios, determining their own level of risk, and making decisions (Zhang et al, 2021). One of the recent events in which a large proportion of the public has been engaged with and responding to visualisations is the COVID-19 pandemic. Quickly-emerging information has been produced to educate the public about the pandemic, make complex mathematical forecasting models easier to understand, and encourage people to alter their behaviour in order to slow the disease's spread (Zhang et al, 2021). As a result, among the most popular and reliable resources for the general public to learn about the pandemic are visualisations. The field of data visualisation is undergoing a number of newer techniques to enable faster interpretation and easier information processing by the public (Few, 2009).

Visual metaphors play an important role in making the transfer of information easier to people. Conceptual Metaphor Theory (CMT) holds that metaphor is the main mechanism through which our thoughts and behaviours are shaped (Lakoff et al, 2003). For example, a flower that is about to blossom symbolises good fortune, and a flower that is about to die symbolises death. Information is processed quickly because users focus on metaphors rather than semantics when interpreting and drawing conclusions, using their limited cognitive resources. On the other hand, when data and metaphorical concepts share casual relationships or relational knowledge, people can achieve cognitive fluency. Glyphs are regarded as iconic or symbolic depictions of one or more dataset variables. The variables that need to be represented can be linked to one or more glyph properties, such as size or colour, by utilising a mapping function (Ropinsky et al, 2011). With that in mind, metaphors have been utilised in many fields to explain the complex dataset. Ropinsky's work on using glyph to represent multivariable medical data is an excellent example to follow. The utilisation of visual metaphors has shown to enhance information retention, but with the trade-off of prolonged processing times (Borgo et al, 2012). Despite this benefit, there has been a surge in complaints about the inaccuracies associated with the depiction of visual metaphors, as highlighted by Tufte et al. Empirical research has underscored that the incorporation of both 2D and 3D visual metaphors does not consistently improve information visualisation.

Achieving effective metaphoric transfer effects in information processing requires meticulous user-centric design. In the present study, we revisit the impact of visual metaphors in information visualisation by employing natural phenomena as metaphors to represent a specific domain (in this case, a disease outbreak). Some research have previously indicated that trend curves used to parameterize natural phenomena in transition animations can strain users' perception, particularly with complex real-world datasets (Würfel et al, 2015). Given this consideration, our study also aims to assess how adept individuals are at adapting to changes within metaphors.

2.Research Questions:

According to Landau et al (Landau et al, 2010), a metaphor has the ability to instantly trigger a range of relevant concepts that can be used to contextualise new information and facilitate understanding. Rather than committing the semantics of visual metaphors to memory, users can direct their limited working cognitive resources toward interpretation and inferences. As a result, they believe that the information presented in metaphors is simple to understand. Although when presented with multiple variables to perceive there seems to be an added complexity for people to view. The research questions are framed in such a way to test out how metaphors aid in the user understanding of data and its metaphoric transfer effects.

- Does the utilisation of natural(weather) metaphors facilitate the understanding of COVID’19 data by the individuals?
    - Are the weather metaphors accurately conveying the relevant COVID’19 data?
    - Can individuals easily identify patterns and hotspots in COVID’19 data by using weather metaphors?
    - Does the usage of weather metaphors have any considerable effects over the errors made by the people?

We also wanted to test how well metaphors can help people to understand the data that is different from the standard techniques.

- If natural(weather) metaphors do enhance the understanding of COVID'19 Information, in what ways do they contribute to better comprehension?

In order to test these research questions, we accordingly hypothesise by:

H0: There is no significant difference in understanding covid data between scientific visualisation and metaphor visualisation

H1: There is a significant difference in understanding covid data between scientific visualisation and metaphor visualisation.

In conclusion, Landau et al.'s insights into the power of metaphors to trigger relevant concepts and enhance understanding align with our research objectives. Drawing inspiration from the belief that metaphors simplify information processing, we seek to assess their effectiveness in conveying the nuances of complex data. Furthermore, our investigation extends to examining how metaphors, if proven effective, contribute to a better understanding compared to standard scientific visualisation techniques ultimately contributing valuable insights to the broader discourse on data communication strategies. The remaining sections of the paper include descriptions of the relevant literature, the stimuli's design, the study's methodology, its results analysis, and our findings along with future works and discussions.

3.Related Work:

3.1 Data Visualisation in Public Health:

Visualisations are essential tools for transforming complex data into insightful representations. They use graphical elements like charts, graphs, and maps to convey information, enabling a deeper understanding of patterns and trends. Data Visualisation has undergone a significant transformation since the development of computer technology. Data Visualisation has become an important part of research in a variety of fields, including algorithms, human perception, animation, and computer vision. Friendly, 2009 defines data visualisation as "information which has been abstracted in some schematic form, including attributes or variables for the units of information" (p. 2). According to Few (Few, 2009), Data Visualisation is subdivided into two categories: information visualisation and scientific visualisation. Information Visualisation is used to visually represent abstract data, such as business data, whereas Scientific Visualisation is used to visually represent physical data (e.g., the human body, the environment, or the atmosphere). Both information and scientific visualisation are concerned with how to transform data into a visual form that can be understood in order to gain insight and knowledge. Geovisualisation, an interdisciplinary field at the intersection of geography, computer science, and information visualisation, focuses on the representation and exploration of spatial data through visual means. Modern cartography involves organising, accessing, and using geospatial information, with maps serving as dynamic portals to distributed data resources, aiding in goal-driven analysis and information synthesis (MacEachren et al, 2000).

Geovisualisation in healthcare has emerged as a crucial tool for understanding spatial patterns and trends in health-related data, offering valuable insights for decision-makers and practitioners. By integrating geographic information systems (GIS) with health data, geovisualisation enables the representation of healthcare-related information in a spatial context. A notable illustration comes from John Snow's maps, which show the correlation between the Broad Street pump and cholera cases (Keith). Notable contributions from public health researchers, such as Jacquez at al, 2010 underscore the importance of geovisualisation in epidemiological studies, enabling researchers and policymakers to identify spatial clusters, hotspots, and disparities in health outcomes. The work of McLafferty and Wang (McLafferty et al, 2011) further emphasises the role of geovisualisation in explaining the spatial determinants of health and facilitating evidence-based decision-making. A number of visualisations have been created by scientists and media outlets to illustrate the pandemic risk due to the rapid and lethal nature of SARS-CoV-2, also known as COVID-19. The COVID-19 pandemic has accentuated the significance of visualisations in shaping public perceptions of risk, emphasising the continued relevance and impact of geovisualisation in our evolving information landscape (Howell et al, 2022)

Displaying results in interactive dashboards, sourced from a diverse range of big data streams, has become a pivotal information resource, particularly during the COVID-19 pandemic. While these web-based dashboards offer almost real-time insights, there exists a potential for errors when users interpret critical information through visualisations. Geovisualisations, which involve the display of spatial information through maps and visual representations, are susceptible to various cognitive and perceptual errors. Misinterpretation can arise due to factors such as the complexity of the visual elements, the use of unfamiliar symbols or colours, and the viewer's prior knowledge and experience. Therefore, it is crucial for researchers to consider human cognitive processes and potential sources of confusion when creating geo visualisations to minimise the likelihood of misinterpretation (Few, 2009).

3.2 Metaphors in Data visualisation:

The use of metaphors in data visualisation are gaining increasing attention in the research world. Maps are an excellent metaphor in the field of cartography to explain spatial data. Metaphors play a pivotal role in enhancing communication and understanding, particularly when dealing with complex data. According to Lakoff and Johnson (Lakoff et al 2003), metaphors are not merely linguistic devices but fundamental cognitive tools enabling individuals to comprehend abstract concepts by relating them to more familiar, concrete experiences. Faced with unfamiliar concepts, our cognitive system seeks the optimal mapping between the unknown concept and previously acquired knowledge in other domains. Metaphors function as bridges between the unfamiliar and the familiar, facilitating comprehension and retention (Zhang, 2008). This process is explained by conceptual metaphor theory, which puts forth that we understand one conceptual domain in terms of another, with metaphors shaping our perceptions and guiding our reasoning (Lakoff et al, 2003).

Metaphors rely on the similarity between the source and target concepts. The target concept is an understanding of something real, concrete, observable, and straightforward. The source domain, in contrast, represents concepts that are complex, abstract, and unfamiliar. Through the use of conceptual mappings, people can reason, interpret, and assess information about the target concept using their understanding of the source concept as a structured framework (Landau et al, 2010). The closest work related to this particular study would be from Li et al, 2015 where the use of metaphoric glyphs in information visualisation is analysed. This study examines how metaphoric transfer effects are dealt on various cognitive activities involved in information processing. Data visualisation using metaphors can evoke schema, a cumulative knowledge that is kept in the user's long term memory, which saves working memory resources, and prevents overload during interpretation. This perceived ease in information processing is called cognitive fluency (Landau et al, 2010). Research by Howell et al, 2022 suggested that using metaphors elicit higher usability among users proving that metaphors can objectively represent information. Information visualisation designers define the meanings of visual tokens using conceptual metaphors, while viewers detect information, recognise meaningful patterns, infer conclusions, and make judgements (Li et al, 2015). Conceptual metaphors go beyond spatial representations and use abstract concepts to communicate information in a relatable way, such as when visualising data trends as a narrative journey (Few, 2009). According to Wurfel et al, 2015 tree maps, commonly employed for visualising hierarchical datasets, prove effective in explaining data trends over time. Wise et al, 1995 employed landscape metaphors, like Themescape, to visualise non-spatial information, such as document themes, representing relationships among documents. They incorporated terrain features like valleys and cliffs to signify the strength of themes.

Metaphors serve as cognitive bridges between complex data and familiar concepts, yet their impact on precision can be nuanced. The precision of a conveyed message in data visualisation is influenced by the choice of metaphor, a critical factor shaping how information is understood. Consider the use of a spatial metaphor like a "tree diagram" to represent hierarchical relationships; this choice can yield a clear and precise understanding of the organisational structure (Few, 2009). Alternatively, employing a metaphor such as "journey maps" to depict temporal data might introduce some abstraction, potentially sacrificing precision for narrative coherence (Cairo, 2013). The precision is further influenced by the audience's familiarity with the chosen metaphor; well-known metaphors can enhance precision by leveraging existing mental schemas, while unfamiliar metaphors may introduce ambiguity. Additionally, the complexity of the data plays a role; a metaphor closely aligned with data structures ensures precision, while a less fitting metaphor might oversimplify or distort the message. In essence, the precision of the conveyed message hinges on the appropriateness of the metaphor selected, emphasising the need for careful consideration based on data nature and audience context. But the trust of information when exposed to metaphor visualisations is not improved.

3.3 Natural Phenomena as Metaphors:

The integration of natural metaphors in visual communication, involving the symbolic representation of complex information through elements from the natural world, is a concept deeply rooted in the cognitive sciences and information design. While the specific term "natural metaphors" may not be extensively cited, foundational works in the field acknowledge the powerful impact of leveraging nature-inspired symbols for effective communication. Cairo's "The Functional Art: An Introduction to Information Graphics and Visualisation" explores the application of metaphors, emphasising the intuitive and relatable qualities of natural elements in data visualisation (Cairo, 2013). Drawing on Lakoff and Johnson's seminal work, "Metaphors We Live By," which delves into the pervasive influence of metaphors on human thought and communication, one can understand the broader theoretical underpinnings of how metaphors, particularly those inspired by the natural world, contribute to shaping perceptions and enhancing the communicative power of visual representations (Lakoff et al, 2003). In essence, the incorporation of natural metaphors serves as a strategic approach to bridge the gap between abstract data and human cognition, fostering a more immediate and meaningful connection with the information being conveyed.

The effectiveness of natural metaphors in visual communication lies in their ability to draw on elements from the natural world, providing familiar reference points that facilitate metaphoric transfer effects and enhance the understanding of abstract concepts. For example, a rising graph metaphorically linked to ascending mountains intuitively conveys the concept of growth or progress. This transfer effect occurs because viewers bring their pre-existing knowledge and experiences with mountains into the interpretation of the data. (Havre et al, 2002) introduced "Themeriver," a visualisation technique designed to represent and analyse thematic changes in extensive document collections in a manner reminiscent of a river. Themeriver aims to offer a visual mechanism for comprehending the evolution of themes or topics over time and across document sets. Although the usage of natural metaphors has been widely spoken, there are no considerable practical applications that use metaphors to explain spatial information.

Glyphs are essential components of visual design because they help metaphorically represent information. According to (Borgo et al, 2013), the term "glyph" generally refers to small, autonomous visual objects that are used to represent data record attributes in a variety of contexts. It can be deduced that information visualisation establishes specific mental associations when employing glyphs to generate and communicate meanings. Notable instances include Pearlman et al, 2007 glyph-based approach to visualise computer network security, employing compound glyphs. An interactive probe-glyph created by De Leeuw et al, 1993 makes it possible to see different flow characteristics in a particular area. Glyphs in geovisualisation helps in easier interpretation of complex spatial data by tapping the glyphs' ability to carry schema information and evoke accumulated knowledge. Beecham et al, 2021 developed DatRS, a glyph-based geovisualisation system for reporting COVID-19 cases, using lines and ridge contours as glyph visual channels while Li et al, 2015 used flower glyphs to represent US educational investments, enhancing understanding and retention of data.

Although natural metaphors in visual communication have many benefits, there may be drawbacks and biases that need to be taken into account. The possibility of oversimplification or misinterpretation is one difficulty. Natural metaphors are by their very nature abstract, and viewers could understand the metaphorical representation in a different way, which could result in misconceptions or oversimplified perceptions of complex data (Li et al, 2015). The processing time is another difficulty. According to Borgo et al, 2012, the use of metaphors may have an impact on users' performance, particularly in target search tasks, as perceptual load is impacted by visual details and features. When creating metaphors based on user performance, careful consideration is required.

3.4 Outbreak Visualisation:

Outbreak visualisation, a critical aspect of epidemiological communication, involves the graphical representation of disease spread and impact. Data collection, analysis, modelling, and visualisations of outbreak data have recently become more complex, resulting in an emerging field of outbreak analytics, where visualisation plays an important role in supporting the understanding of complex outbreak data (Jonathan et al, 2019). Utilising effective data visualisations help communicate the dynamics of an outbreak, illustrating patterns of transmission, geographic distribution, and the progression of the disease over time (Budd et al, 2020). Well-designed outbreak visualisations enhance public understanding and awareness, aiding in the dissemination of crucial information for timely response and intervention. Notable works in data visualisation, such as those by Tufte, 2001 and Cairo, 2013 emphasise the importance of clear, informative, and ethical visual representations, underscoring the role of outbreak visualisations in shaping public perceptions and influencing decision-making during health crises.

The COVID-19 pandemic has emphasised the importance of online dashboards for providing spatial information on infections, deaths, and hospitalizations (Ahasen et al, 2020). Public trust during a pandemic is crucial for effective intervention, necessitating education, cooperation, and a suitable communication strategy (Budd et al, 2015). During the COVID-19 outbreak, map centric dashboards created by Johns Hopkins CSSE, the WHO and many other notable organisations went viral, informing both the general public and health professionals (Boulos et al, 2020). Ahasan et al, 2020 acknowledged the successful implementation of the COVID-19 dashboard by Johns Hopkins University that effectively integrates data from diverse sources, showcasing its proficiency during the pandemic. HealthMap provides real-time updates on pandemic progression by utilising dot maps. Budd et al, 2020 used the heat map technique in GIS to show the global spatial distribution of COVID-19 cases. Lan et al, 2020 used bivariate maps to address the risk associated with

COVID-19 by taking into two variables (death rate and population density). Animated maps enable end users to be faster at detecting patterns and more accurate at remembering those patterns (Griffin et al, 2006) and trends (Cinnamon et al, 2009). These visualisations enhance data transparency, aids authorities in communicating crucial information, and fosters increased awareness and sensitivity among the public (Pardo et al, 2020).
Even though we frequently encounter various visualisation methods and have learned about the advantages of employing metaphors in medicine (Rozinsky et al, 2011), there hasn't been much research on the application of metaphors in relation to pandemic diseases like COVID-19. This study aims to explore the metaphoric transfer effects of weather metaphor glyphs in comprehending COVID-19 data. The goal is to assess how these chosen metaphors impact usability and understanding, particularly in comparison to established standard visualisations commonly encountered in previous outbreak visualisations.

4. Experimental Overview:

Although visual metaphors have been explicitly studied over the years, there have been few empirical studies in using metaphors for information processing and most of the work has remained theoretical. Not many people explored the idea of using natural metaphors to explain data in the form of a journey that closely resembles an existing phenomenon. Information Visualisations typically involve the simultaneous examination of two or more variables, posing a challenge for inexperienced users who must quickly recall numerous mappings. Even for experts, making a decision when there are multiple factors to take into account can be challenging. Works by Beecham et al, 2021 used glyphs for multivariate COVID-19 datasets, drawing inspiration from Ropinsky's research. Despite frequent mention, the utilisation of natural phenomena as metaphors remains largely unexplored, particularly within the healthcare industry. This study aims to investigate how natural metaphors are perceived and comprehended, their impact on user performance in geo visualisations, their efficacy in explaining extensive datasets across large regions, and multiple variables. By examining how natural metaphors affect users' performance in visualisations, this study seeks to ascertain whether they can successfully simplify large and complex data sets.

When displaying epidemiological data, like COVID-19, we must be careful about the types of data we choose to display and the manner in which we do so. This study aims to assess the impact of natural metaphors compared to traditional standard visualisations. For standard visualisation, we opted for widely recognized representations such as choropleth, bivariate, and pattern maps (Fig 1). These choices prioritise simplicity, ensuring that all participants can easily comprehend the fundamental statistical representations crucial for this study. An additional consideration in selecting visualisation techniques is their ability to represent multiple variables concurrently. Employing the aforementioned techniques for standard visualisations facilitates the clearer explanation and layering of multiple variables.

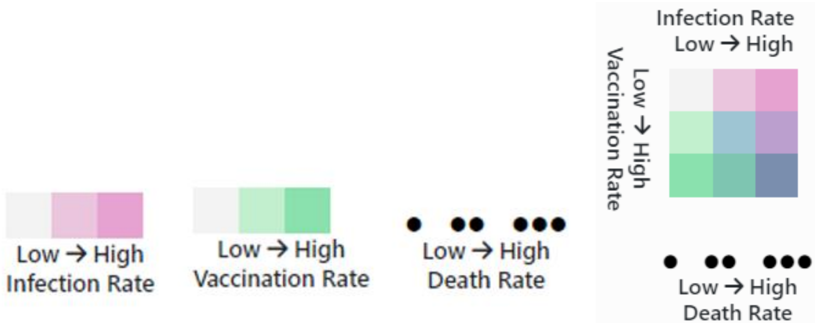

Fig 1: Parameterization of Standard Visualisations in univariate and multivariate visualisations

Benking and Judge (Benking et al, 1994) categorised spatial metaphors into six groups, and one of these categories includes natural forms. When people encounter similar features, structures, and causal relationships, they draw inferences about the target concept based on their existing knowledge (Lakoff et al, 2003). In this study, we aim for a metaphorical representation that spans a broad spectrum and resonates strongly with people. To achieve this, we've chosen weather phenomena as a metaphor to represent COVID-19 data. To improve stimulus reliability, a small but ethnically diverse group of people looked at the selected visual metaphors. In our experiment, we kept our metaphorical and non-metaphorical stimuli in a one-to-one visual setting (i.e, each task will contain both types of visualisations).

4.1 Design and Parametrization of Natural Metaphors

A metaphor is made up of the following elements: a target domain, a target item, a source domain, a source item, and a matching part (MacEachren et al, 2000). This section describes how we mapped natural phenomena to COVID-19 data before turning them into appropriate metaphors and parameterization (Fig 2). The source item (for example, rainfall) from a well-known source domain (natural phenomena) is mapped to the target domain's target items (infection rate). The target domain (disease outbreak) is new, and the match will never be perfect. The larger the matching part, however, the better the metaphor works (Few, 2009). Initially, we intended to represent weather phenomena as they occur in the real world (as realistic effects), but doing so introduces technical challenges that impose a time constraint. So, using glyph-based weather elements solves the problem due to its metaphorical nature. This was discussed in chapter 3 in detail. In our analysis of COVID-19 data, we focus on key variables, namely the infection rate, death rate, and vaccination rate. These parameters are widely featured in various visualisations, aiding people in swiftly and effectively comprehending the situation. When selecting metaphors, it's crucial that they offer familiar reference points for people to grasp the underlying data rather than focusing solely on the metaphors themselves. Automatic parameterisation is essential for adapting the metaphor to the evolving nature of the data, ensuring that it effectively communicates the nuances of the COVID-19 situation to the audience. When choosing the metaphor visualisations, we wanted to satisfy the same requirements that we have chosen for the standard visualisations: familiar visualisations and the ability to explain multiple variables at once.

In this study, we choose the intensity of rainfall metaphorically to signify the severity of the infection rate. A higher intensity aligns with a rapid and widespread infection outbreak, while a lower intensity symbolises a slower or more localised spread. We selected rainfall because it signals the start of a strong storm, just as infection rates signal a pandemic's commencement. It's also crucial to consider the hierarchy within datasets, particularly the sequence in which events unfold over time. For instance, the occurrence of death tolls aligns with the peak of COVID-19 infections. Therefore, when choosing metaphors, it's essential to opt for ones that highlight this escalating intensity. In this context, considering rainfall, we employed the metaphor of a lightning glyph. This choice not only represents the intensifying nature of the data but also taps into the ominous connotations associated with lightning across various cultures, emphasising its association with something more perilous. The timing of the lightning flashes symbolises the intensity of death cases. In a similar vein, we used the metaphor of sunshine to explain the vaccination rate, which occurs later as a defensive measure against infection and death rates where clear sun signifies highest vaccination. This metaphor represents the end of the metaphorical "rainfall" of infections and "lightning" of deaths, providing a sense of hope reminiscent of the clearing skies after a calamitous event.

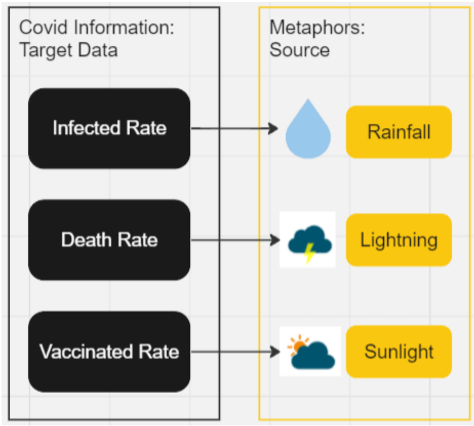

Fig 2: Mapping of natural phenomena(Source domain) to the COVID-19 data(Target domain)

4.2 Data Source

Given the numerous discrepancies and higher susceptibility to errors in real-life data, we have opted to utilise simulation data for this study. The data consist of simulation results derived from hybrid models that integrate SIR-type models on local scales with spatial resolution (Koslow et al, 2022). This compartmental model uses age stratification and spatial resolution to represent reality. The RKI, 2021 and DIV, 2020 databases are used to extrapolate the number of people in each compartment at the start of the simulations. The model comprises 21–27 distinct infection states (compartments) representing different stages of individuals in the context of SARS-CoV-2 (Betz et al, 2023). These compartments include Susceptible (S) individuals without prior exposure to the virus, Exposed (E) individuals carrying the virus but not yet infectious, Carrier (C) individuals infectious to others but not showing symptoms, Infected (I) individuals infectious and displaying symptoms, Hospitalised (H) individuals with a severe manifestation of the disease, and those who unfortunately succumb (Dead - D). Additionally, Recovered (R) individuals are considered immune. The vaccinated compartment that we wanted to visualise in this study was calculated from the formula below

$$\sum(i_{V1}+i_{V2})) \;/\; \sum(i) \qquad \text{(i)}$$

where i is the different infection states, V1 and V2 are the infection states that have been vaccinated once and twice. Simulations spanning 90 days from June 06, 2021, are accessible for every administrative district within Germany. However, for the purposes of this study, we have opted to utilise two distinct dates due to the consideration of temporal variations falling beyond the intended scope of this study. The full code for this hybrid model can be found at (Abele et al, 2021).

4.3 Implementation Overview

In the development of visualisations for this study, we employed HTML canvas considering performance capabilities to draw the metaphor animations, the d3.js library to draw the map from geojson file, and amCharts for creating standard visualisations. Our primary objective was to compare non-metaphoric and metaphoric visualisations, both in isolation and in combined forms for user readability. The design process involved iterative testing of these metaphors, with multiple feedback sessions conducted within a small group.

During the creation of each metaphor, specific requirements were adhered to:

1. Alignment with COVID-19 Information:

Selected weather metaphors were carefully chosen to align with the relevant COVID-19 information. For instance, in representing infection rates with rainfall, we considered frequency as the defining feature, opting for animation maps to convey intensity dynamically. This was also to understand how people can handle the changes within metaphors and its impacts of user experience which studies from (Würfel et al, 2015) and (Borgo et al, 2013) noted.

Fig 3: Design and Parameterisation of Weather Metaphors

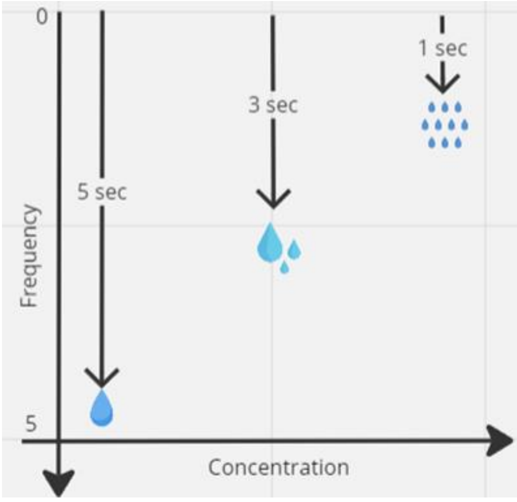

Fig 4: Frequency and Concentration of Rainfall representing Infection Rate

2. Single Defining Feature:

Each metaphor was designed to have a singular defining feature to prevent confusion. For instance, connecting lightning with the duration of lightning flashes to symbolise death rates, we opted for slower disappearance of flashes (high prominence) instead of frequent flashes for high death rates (Fig 5). This decision was influenced by rainfall metaphor, where the frequency feature was utilised to signify infection rates. The management of visual complexity involved incorporating reflective arcs against the cloud, mirroring occurrences in the natural world. Thus, the combination of duration and reflective arcs of lightning flashes are considered one defining feature of lightning metaphor collectively conveyed death rates.

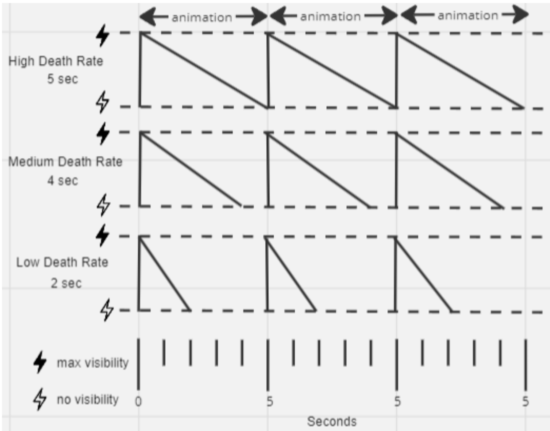

Fig 5: Frequency of lightning flashes for Lightning metaphor representing Death Rate

3. Distinctive Features across Multi Variables:

Avoidance of matching defining features was crucial when representing multi variables. When parametrizing sunlight, we decided against using colour variations to represent vaccination rates. This choice was made to prevent users from gaining knowledge about how to interpret the data by using colour scale, which were used in one of the standard visualisations (a choropleth map). Instead, we opted to symbolise vaccination rates through the degree of sun placement. We used x, y and z translation commonly used in weather forecasts for sun placement to represent vaccination rates Fig 6.

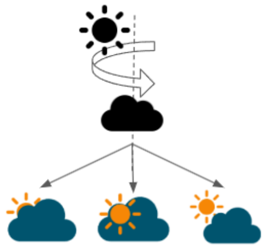

Fig 6: Rotation of Sun with respect to cloud representing Vaccination Rate

4. Cohesiveness in Combined Metaphors:

The integration of metaphors was approached with a focus on cohesiveness. All three selected metaphors, rooted in the weather domain, form a unified narrative that mirrors the unfolding events of COVID-19 (Fig 7). This contextual consistency facilitates easier comprehension and connection-making for viewers. This meticulous approach to the implementation process ensured that each metaphor served its purpose distinctly and collectively contributed to a comprehensive understanding of COVID-19 dynamics. The considerations regarding alignment, singularity, distinctiveness, and cohesiveness underscore the effectiveness of the visualisations in conveying complex information.

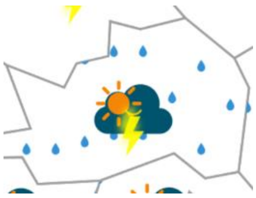

Fig 7: Integration of the three weather metaphors to visualise multivariate COVID-19 data.

5. Experiments

We have designed experiments to test the hypotheses proposed in the research question section and report in this section.

5.1 User Study design

In accordance with Chapter 2's Research Questions, we devised a within-subject experimental design to assess our hypothesis. The principal aim of this study is to analyse the effects of employing natural metaphors in the visualisation of COVID-19 data. The core hypothesis stated below revolves around understanding the significance of using metaphors compared to conventional visualisations.

(Alternative) H1: There is a significant difference in understanding COVID-19 data between each metaphor and standard visualisations.

As highlighted by Würfer et al, 2015, processing time for users can be significantly prolonged when dealing with changes within metaphors. To investigate these assertions, we formulated the following hypotheses:

(Alternative) h1: There is a significant difference in cognitive demand when processing information using each metaphor and standard visualisations.

If the type of visualisation (metaphoric and standard) is independent of the understanding level of COVID-19, the h1 hypotheses can provide if higher cognitive processing takes place for performing the tasks. Given the effectiveness of metaphors in representing multivariate data (Ropinsky et al, 2011), we aimed to compare the performance of these weather metaphors to conventional visualisations to see if there was any difference in comprehension and ease of readability of COVID-19 data.

(Alternative) H2: There is a significant difference between standard and metaphor visualisations in understanding multivariate COVID-19 data

(Alternative) H3: There is a significant difference in readability of multivariate COVID-19 data between standard and metaphor visualisations.

5.2 Stimuli design

As the stimuli for this experiment, we created two versions of data visualisation representing COVID-19 data. Three variables are displayed: infection rate, death rate, and vaccination rate. The participant will be exposed to both types of visualisations in order to determine which type of visualisation works best. Using a within-subject design we can reduce individual variations and increase the statistical strength by involving the same participants in different situations. To comprehensively evaluate how each metaphor performs independently and in combination, participants will engage in two segments (parts), experiencing the metaphors individually and in combined formats. In both scenarios, participants will initially encounter standard visualisations for a baseline assessment. Each visualisation will have its own legend explaining the defining features to understand the COVID-19 data.

5.3 Assignment A

The Assignment A will test both forms of visualisations individually. Within Assignment A, users will perform 3 sub tasks. In total, we will have 6 map visualisations (stimuli) out of which 3 are weather metaphors. To assess the hypothesis (H1 and h1) in a standardised experimental setting, we utilise a fundamental multiple-choice question-and-answer format to measure participants' performance in terms of accuracy, errors, and mental demand. This straightforward format is universally recognized by all participants, minimising the need for extensive learning efforts.

Subtask A: Metaphor Infected Rate (Rainfall) vs Standard Infection Rate (choropleth map)
Subtask B: Metaphor Death Rate (Lightning) vs Standard Death Rate (pattern map)
Subtask C: Metaphor Vaccination Rate (Sunlight) vs Standard Vaccination Rate (choropleth map)

Some of the confounding factors must be avoided in this stimulus's design. Such as:

• Sequence bias – The order in which stimuli are presented during the study could influence both positive and negative effects on later-presented stimuli (e.g., through learning).

• Focus bias – Participants may inevitably face fatigue or lapses in attention, potentially impacting their performance at different stages of the study.

• Cultural bias - Metaphors are often context-dependent. The context in which a metaphor is used, as well as the cultural context of the audience, can significantly influence how it is understood.

• Recall bias - Potential distortion or inaccuracy in the recollection and interpretation of metaphors by individuals.

Similar to the majority of empirical studies, it's challenging to entirely eliminate these confounding effects. However, efforts should be made to minimise them to a degree where their impact on participants' performance is not significantly noticeable. Since it's not feasible to utilise identical data for various stimuli, we meticulously crafted each pair to guarantee the display of comparable concepts, maintain similar visual designs (except for metaphorical elements), and present an equivalent level of cognitive load. We utilised two different dates for the type of visualisations to avoid sequence bias. As the entire user study may take approximately 25 to 40 minutes, participants have the option to take breaks and resume later to alleviate fatigue and reduce focus bias. The stimuli are presented in pairs and randomised to avoid sequence bias such as ABC, BCA and CAB, with the standard visualisation being the first encountered by participants.

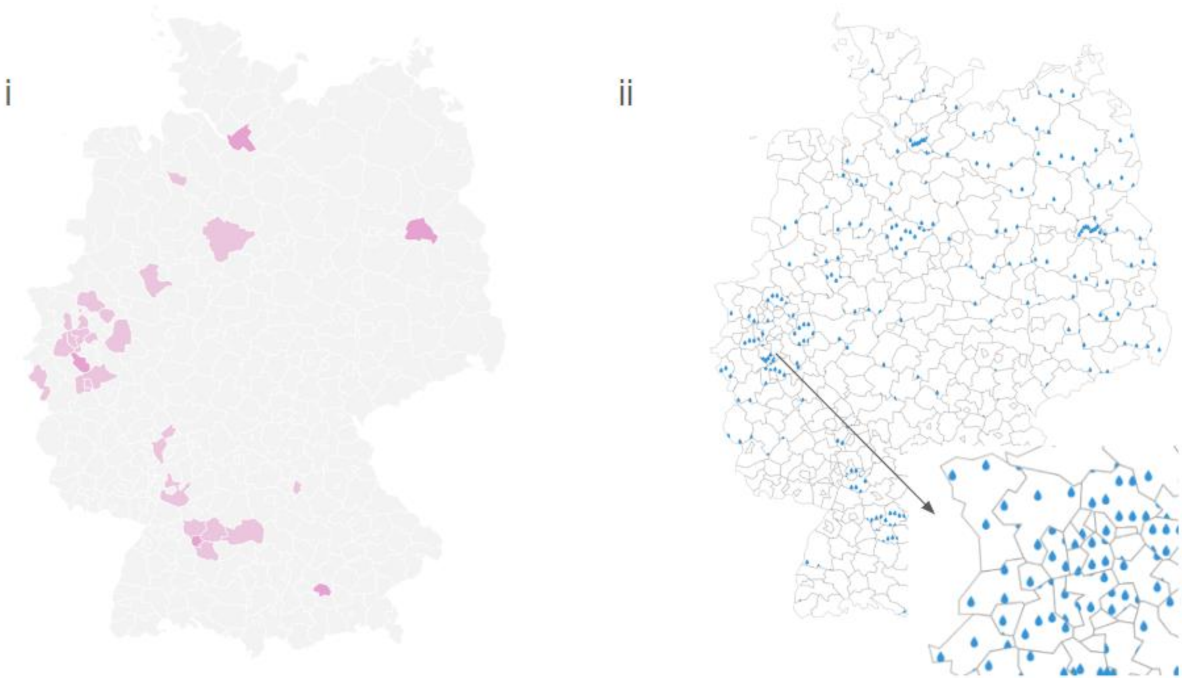

Fig 8: Stimuli Standard Visualisation for Assignment A - Subtask A (i) standard infection rate (ii) metaphor infection rate

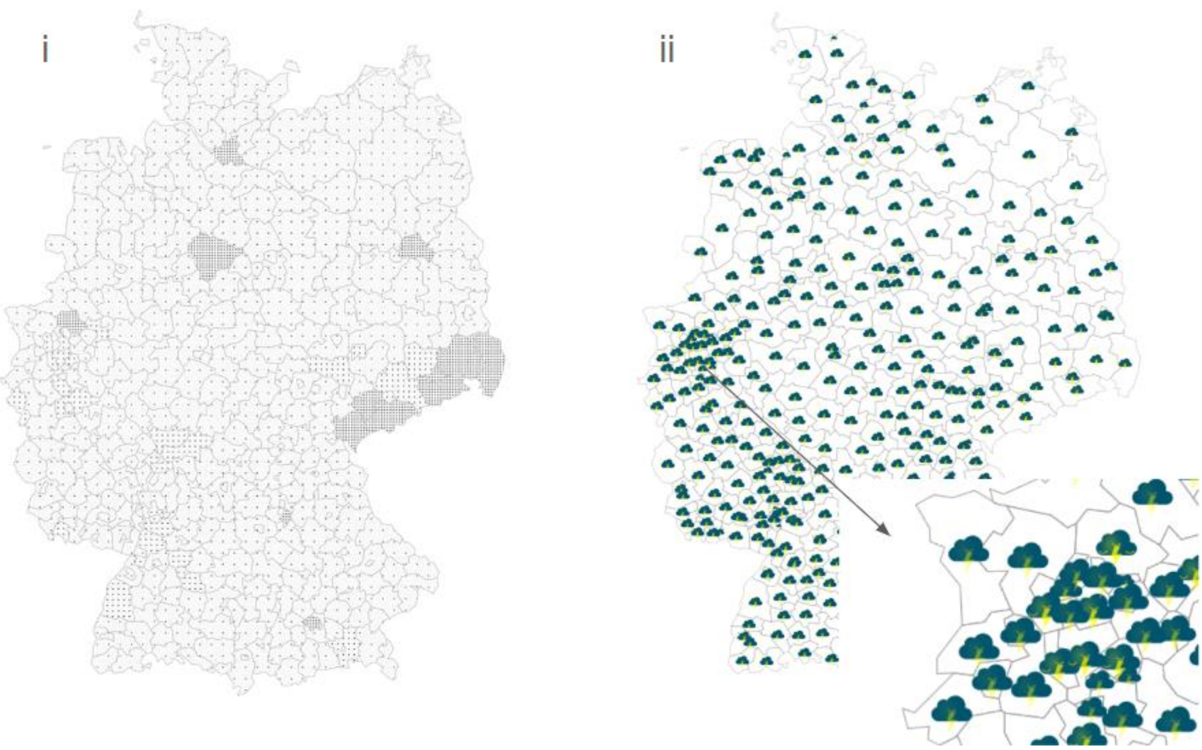

Fig 9: Stimuli Metaphor Visualisation for Assignment A - Subtask B (i) standard death rate (ii) metaphor death rate

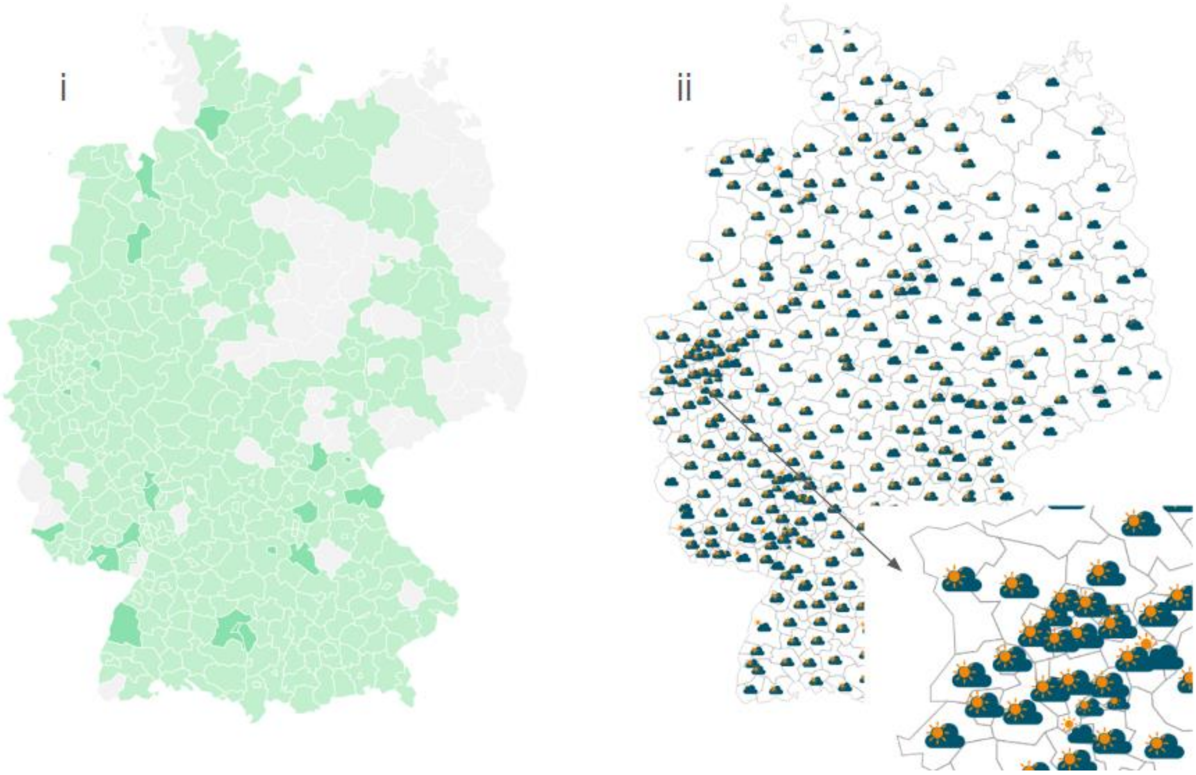

Fig 10: Stimuli Metaphor Visualisation for Assignment A - Subtask C (i) standard vaccination rate (ii) metaphor vaccination rate

5.3.1 Questionnaire

We have crafted a questionnaire comprising four categories of questions to evaluate participants' abilities in visual information processing fluency, accuracy of inferences, mental demand and confidence in information processing. The questions are both standard and metaphor visualisations are different but follow the same category. The first type of questions from Q1-3 are designed to measure participants' ability to identify extremities by comparing two or more districts in the map visualisation and evaluate whether participants can accurately state the COVID-19 data for specific districts to assess the primary hypothesis (H1). The second set of questions Q4 aims to quantify participants' cognitive load (mental demand) during these tasks using the visualisation, following a format similar to NASA TLX but employing a 3-point scale instead of 7. To measure User Experience, Participants will share their thoughts on how satisfied they are and how difficult they think it is to use these visualisations for performing the said tasks. Participants will also evaluate the natural metaphors and choose their favourite metaphor at the end. The purpose of this step is to comprehend the meaning behind each metaphor that people have selected. The majority of questions in the survey adopt a Likert scale (Jebb et al, 2021) to evaluate user experience. The entire questionnaire for Assignment B is listed in the appendix.

5.4 Assignment B

Assignment B focuses on assessing participants' user readability and how metaphor and standard visualisations are able to deal with multiple variables simultaneously. Each participant will encounter two stimuli, one of each form of visualisations presented in a combined format. To ensure a fair comparison between the two visualisations, we strive to create a cohesive design for both standard and metaphor visualisations. For standard visualisation, we used patterns with bivariate maps. For the glyph-based metaphor visualisation we effectively combined three weather metaphors as shown in (Fig 11). Participants will first see the standard visualisation, just like in Assignment A. We employed the learning bias that participants will encounter from Assignment A as a learning curve for Assignment B to compensate for the knowledge bias that the standard visualisation has for fair comparison. We kept the data consistent for both visualisations but randomly assigned the questions to ensure an equal cognitive load and reduce the confounding bias introduced in Assignment A. Multivariate Visualisations highlight variable interactions that may not be apparent in univariate or bivariate analyses. It is essential to evaluate the overall situation in order to fully understand the data in accordance with Hypothesis H2.

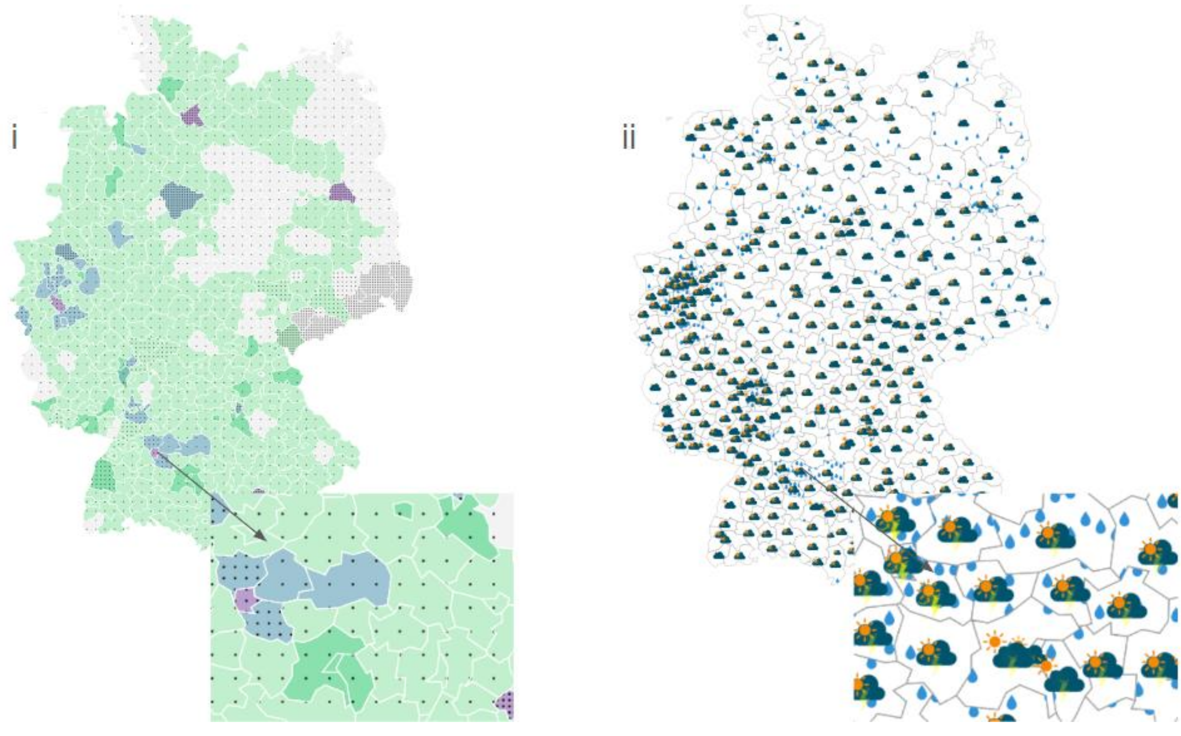

Fig 11: Stimuli visualisation for Assignment B (i) Combined Standard Visualisation (ii) Combined Metaphor Visualisation comprising all three visualisation techniques respectively.

5.4.1 Questionnaire

We centred our questions around a similar theme from Assignment A: mental demand and quantitative and qualitative assessments (Q1-3). Here Though, we also aimed to evaluate whether or not participants could better comprehend the general state of COVID-19 after being exposed to three different variables (vaccinations, deaths, and infections) in a single scenario. For instance, in order to determine which type of visualisation is most effective, we have inquired about the spatial distribution of a single variable (infection rate) in both visualisations (Q4a). Following the task questionnaire, participants will be required to respond to a series of questions concerning the visualisations' perceived readability and ease of use which follows a 5-point Likert scale (Jebb et al, 2021). The entire questionnaire for Assignment B is listed in the appendix.

5.5 Main Study

We conducted an on-line survey using the service at https://www.limesurvey.org/. The sample, comprising 36 individuals randomly selected primarily from Germany, participated in the experiments. Out of 36 individuals we selected 30 individuals to have an equal number of Subtasks (ABC) to analyse. Individuals aged 18 and up are eligible to participate. Data from participants are collected anonymously, and they have the option to resume the survey at their convenience. No significant difference in education level is found between the participants. The responses collected are formatted in Excel. Before applying statistical methods, it is essential to ensure that the collected data pass normality tests. Various tests, including histograms, box plots, Q-Q plots, and statistical methods, can be employed to check for normal distribution. For this study, we used Q-Q plots (Fig 12) and the Shapiro-Wilk test (Table 1) to assess normality. Both the tests have shown that the data is not normal and hence we need to move on using non-parametric statistical methods. The respective data plots are presented below.

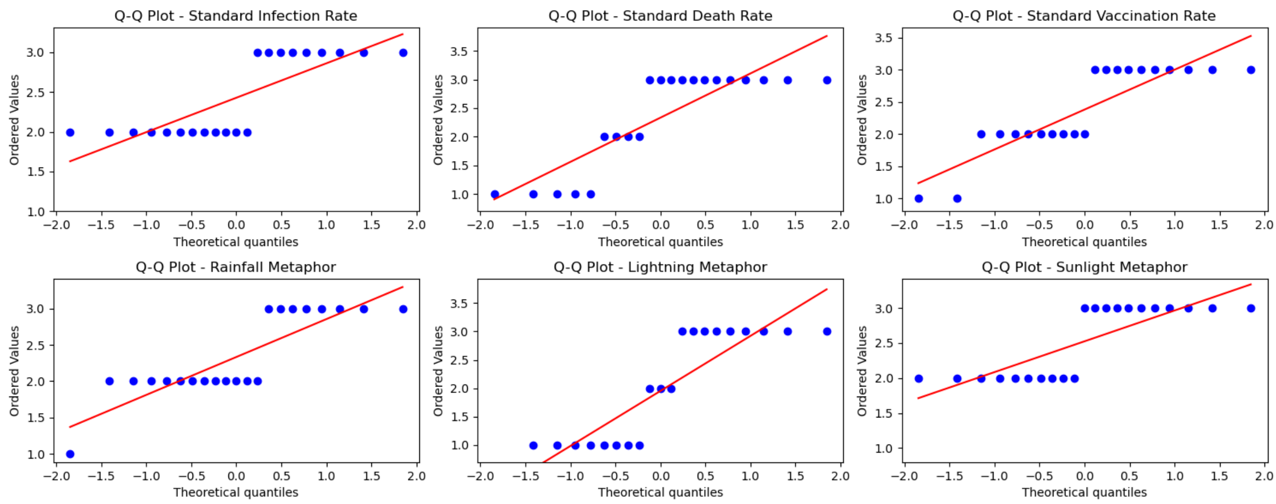

Fig 12: Q-Q Plots for all the standard and metaphor visualisations (top row for Standard Visualisations, bottom row for Metaphor Visualisations).

Shapiro Result	statistic	p value
Standard Infection Rate	0.6331965327	0.0000
Standard Death Rate	0.7109466195	0.0000
Standard Vaccination Rate	0.7648269534	0.0002
Rainfall Metaphor	0.7381496429	0.0001
Lightning Metaphor	0.7927443385	0.0005
Sunlight Metaphor	0.6398172379	0.0000

Table 1: Shapiro Wilk test for standard and metaphor visualisations (p-value <0.05 indicates that data is non-parametric)

6. Results and Analysis

6.1 Hypothesis 1: Understanding COVID-19 data

To test our hypothesis, we employed the Chi-Square Test of Independence to examine whether a correlation exists between the type of visualisations (Standard vs. Metaphor) and the Level of Understanding (High vs. Low) for each subtask for COVID-19 data. To conduct the Chi-Square Test of Independence, we constructed a contingency matrix representing the frequency of data points in each cell. Three questions (Q1-3) from Assignment A were utilised to assess participants' quantitative and qualitative reasoning. The Chi-square test between each subtask (standard vs metaphor) reveals (Table 5): (i) Subtask A (p = 0.7921), (ii) Subtask B (p =0.4345), (iii) Subtask C (p = 0.6054). The p-value for each subtask exceeded the alpha threshold of 0.05, leading to the rejection of the alternative hypothesis (H1). We examined the means of each metaphor visualisation (Table 5) in Assignment A for comparing correctness of Information for the Question 1-3: (i) Subtask1 (mean = 2.27), (ii) Subtask 2 (mean = 2.17), (iii) Subtask 3 (mean = 2.53). When comparing the means of both standard and metaphor visualisation (Table 5): (i) Subtask 1 - 2 reveals a higher means for standard visualisation techniques. (ii) Subtask 3 reveals a higher means (mean = 2.53) for sunlight metaphor.

Type of Visualisation	High Understanding	Low Understanding	Total (Frequency)
Standard Infected Rate	13	17	30
Metaphor Infected Rate (Rainfall)	11	19	30
Total (Frequency)	24	36	60

Table 2: Chi-Square Contingency matrix of grid 2 x 2 for Infected Rate

Type of Visualisation	High Understanding	Low Understanding	Total (Frequency)
Standard Death Rate	19	11	30
Metaphor Death Rate (Lightning)	15	15	30
Total (Frequency)	34	26	60

Table 3: Chi-Square Contingency matrix of grid 2 x 2 for Death Rate

Type of Visualisation	High Understanding	Low Understanding	Total (Frequency)
Standard Vaccinated Rate	13	17	30
Metaphor Vaccinated Rate (Sunlight)	16	14	30
Total (Frequency)	29	31	60

Table 4: Chi-Square Contingency matrix of grid 2 x 2 for Vaccinated Rate

No	Subtasks	Mean	Std.Dev	p value
A	Standard Infected Rate	2.40	0.55	0.7921
	Metaphor Infected Rate (Rainfall)	2.27	0.63	
B	Standard Death Rate	2.50	0.72	0.4345
	Metaphor Death Rate (Lightning)	2.17	0.93	
C	Standard Vaccinated Rate	2.33	0.65	0.6054
	Metaphor Vaccinated Rate (Sunlight)	2.53	0.50	

Table 5: Chi-Square Test of Independence for each standard and metaphor visualisation

6.2 Hypothesis h1 - Cognitive Demand

For analysing the subjective difficulty in performing the tasks in Assignment A, we used wilcoxon signed rank test. This test was chosen due to the dataset being ordinal and continuous. Question 4 was used to measure the mental demand of participants to complete the task questions 1-4 having been exposed to the respective visualisations. The analysis (Table 6) revealed a significant difference in cognitive demand for all Subtasks ($p = 0.0047$, $p = 0.0003$, $p = 0.0049$) rejecting null hypothesis (h0). The means of each metaphor visualisation (Table 6) from the subtasks are shown to examine the source of the difference: (i) Subtask A (mean = 1.83), (ii) Subtask B (mean = 2.43), (iii) Subtask C (mean = 1.83).

No	Subtasks	Mean	Std.Dev	p value

A	Standard Infected Rate	1.40	0.55	0.0047
	Metaphor Infected Rate (Rainfall)	1.83	0.64	
B	Standard Death Rate	1.70	0.69	0.0003
	Metaphor Death Rate (Lightning)	2.43	0.84	

No	Subtasks	Mean	Std.Dev	p value
C	Standard Vaccinated Rate	1.43	0.56	0.0049
	Metaphor Vaccinated Rate (Sunlight)	1.83	0.73	

Table 6: Wilcoxon signed rank test for each standard and metaphor visualisation

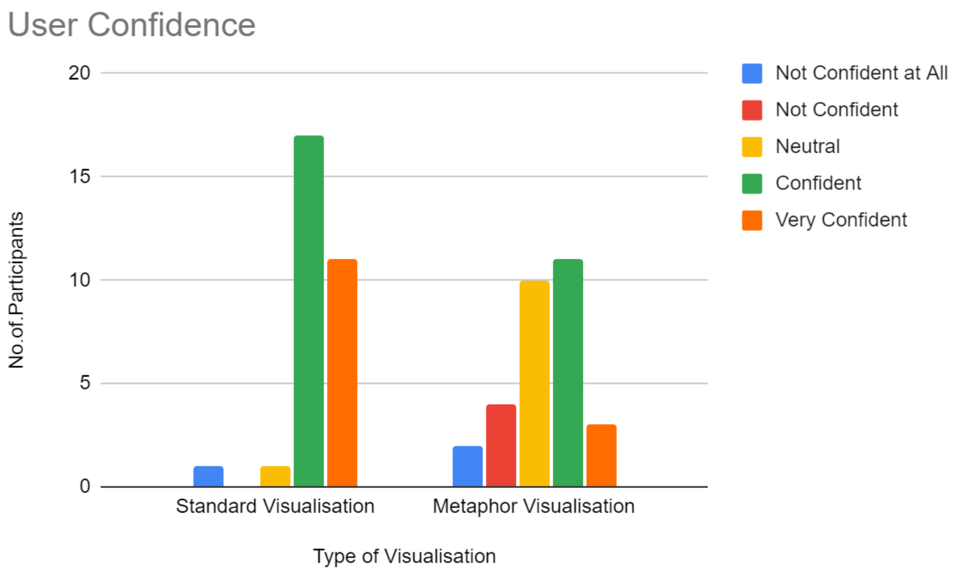

Fig 13: User Confidence for standard and metaphor visualisations

6.3 Hypothesis H2 - Understanding Multivariate COVID-19 data

The second part of the user study aims to evaluate the effectiveness of standard and metaphor visualisations in representing Multivariate COVID-19 data. Participants will be required to answer Question 1-4 from Assignment B which measures qualitative, quantitative reasonings and overall assessments of the condition. Since the dataset for the study is non-parametric (see Fig 14), we will use Fisher's test. Fisher's test was used instead of the chi-square test of independence since the dataset is rather small. To use the chi-square test of independence one has to have a minimum of 5 data points within each category. For the fisher's test, the p-value must be greater than significant level (0.05) to reject the null hypothesis (Kim 2017). The contingency matrix for performing the fisher tests is presented below (Table 7) The analysis (refer Table 8) indicates a p-value of 0.18 (p>0.05), indicating significant difference supporting the alternate hypothesis (H2).

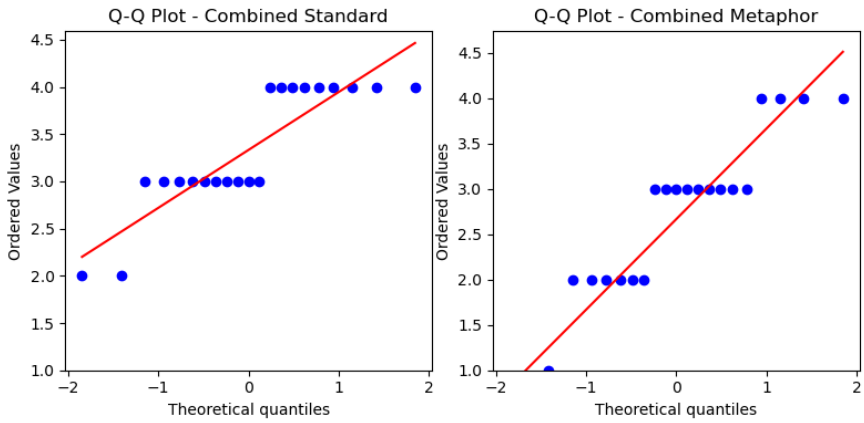

Fig 14: Q-Q Plot for both Combined forms of Visualisation

Type of Visualisation	High Understanding	Low Understanding	Total (Frequency)
Combined Standard Visualisation	14	16	30
Combined Metaphor Visualisation	8	22	30
Total (Frequency)	22	38	60

Table 7: Fisher's contingency matrix of grid 2x2 for combined visualisation

No	Tasks	Mean	Std.Dev	p value
1	Combined Standard Visualisation	3.33	0.70	0.18
	Combined Metaphor Visualisation	2.87	0.96	

Table 8: Fisher's test for combined visualisation

To further examine the correctness of answers, we compare the means of combined visualisations (Table 8) which shows that combined standard visualisation has a higher mean (Mean = 3.33) than combined metaphor visualisation (Mean = 2.87). For Question 1-3 there is not much difference between correctness of information. In Question 4 however assessing overall assessment, the no. of correct answers are shown below:

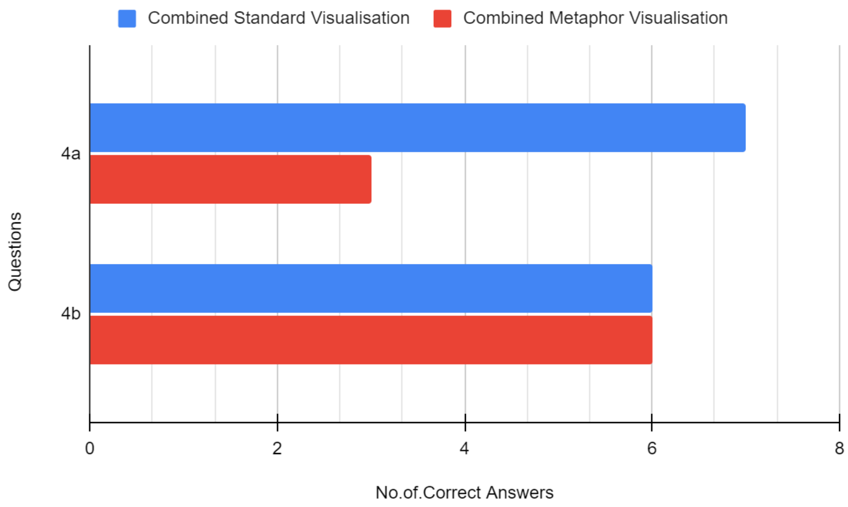

Fig 15: The rate of correctness of information interpretation (Questions 4a and 4b)

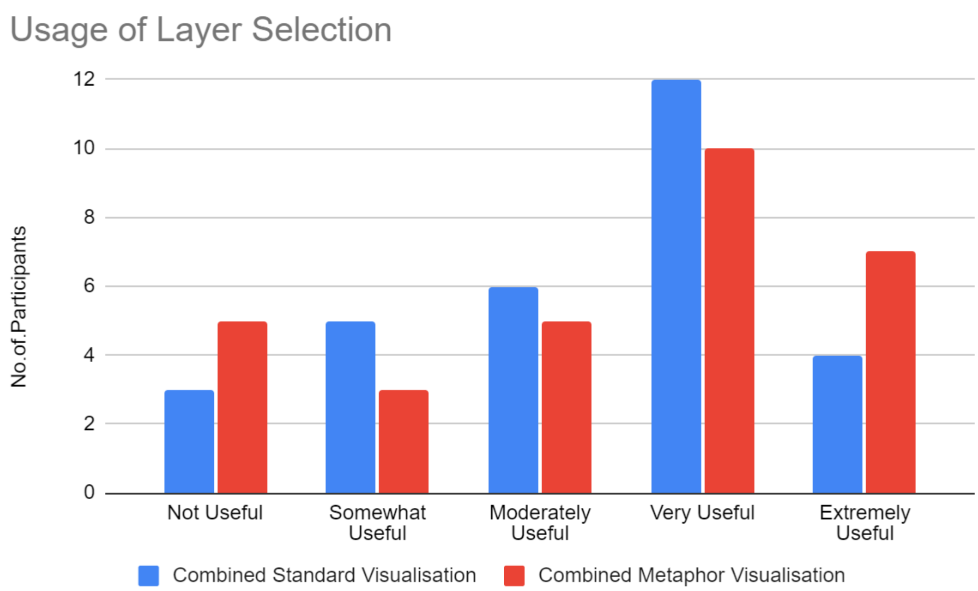

Fig 16: Usage of Layer Selection in Visualising Multivariate COVID-19 Data

There is a significant difference to assess the subjective difficulty for both multivariate (Assignment B) and univariate visualisations (Assignment A), we examined wilcoxon test of significance which revealed that there is no significant difference between cognitive demand between univariate and multivariate visualisations. In Assignment A, we computed the means of standard and metaphor visualisations separately to compare them with the means of combined visualisations (Table 10). The results suggest for average standard visualisation ($M = 1.49$), the mean is lower than that of the combined standard visualisation ($M = 1.93$). Conversely, for metaphor visualisations, the average metaphor visualisation ($M = 2.09$) mean is higher compared to the combined metaphor visualisation ($M = 1.52$). When we look into the subjective difficulty of participants (Table 9), the combined metaphor visualisation has higher means (Mean = 2.47) than standard visualisation (1.93).

No	Tasks	Mean	Std.Dev
1	Combined Standard Visualisation	1.93	0.57
	Combined Metaphor Visualisation	1.52	0.72

Table 9: Cognitive Demand of participants over Combined Visualisations

No	Subtasks	Mean	Std.Dev	p value
1	Averaged Standard Visualisation	1.49	0.56	0.002
	Combined Standard Visualisation	1.93	0.57	
2	Averaged Metaphor Visualisation	2.09	0.66	0.005
	Combined Metaphor Visualisation	1.52	0.72	

Table 10: Cognitive Demand of participants over Univariate and Multivariate Visualisations

6.4 Hypothesis h2 - Readability

The second part of the Assignment B was to analyse if there exists a significant difference between readability of the visualisations for information processing. To prove this hypothesis (h2) we use wilcoxon signed rank test once again since the dataset is a 5-point likert's scale. The analysis revealed that the tasks represent a significant difference (p-value = 0.001) rejecting the null hypothesis. When comparing the means of the combined standard visualisation has higher mean (Mean = 3.17) than that of metaphor visualisation.

No	Tasks	Mean	Std.Dev	p value
1	Combined Standard Visualisation	3.17	0.97	0.001
	Combined Metaphor Visualisation	2.13	1.09	

Table 11: Wilcoxon signed rank test for combined visualisation

To further test if there is a relationship between readability and the cognitive demand of the participants in understanding multivariate data, we used spearman's correlation coefficient. It picks monotonous relationships easier. The rho value will be between (-1 to +1) suggesting negative and positive associations. The results suggest a positive relationship: standard visualisation (rho = 0.11) and a positive relationship for metaphor visualisation (rho = 0.47).

Type of Visualisations	Spearman's correlation coefficient (rho)
Combined Standard Visualisation	0.11
Combined Metaphor Visualisation	0.47

Table 12: Spearman Correlation Coefficient for combined visualisations

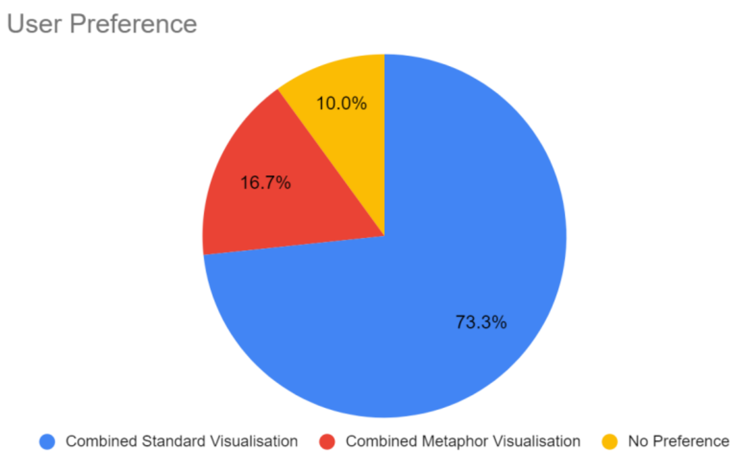

Fig 17: User Preference over readability of Multivariate Data

7. Findings and Discussion

Information Processing for Univariate COVID-19 Data

The choice of visualisation setting (standard vs. metaphor) for each subtask in Assignment A implies that the type of visualisations used for each subtask is unrelated to the comprehension of COVID-19 data rejecting our hypothesis (H1). This indicates that the weather metaphors do not significantly impact information processing for the participants. When we looked into the means of correctness for Question 1-3, the results are somewhat similar to that of standard visualisation techniques. When examining the means of correctness for Question 1-3, it was evident that the use of the Sunlight metaphor, as opposed to the choropleth standard visualisation technique, resulted in higher correctness of information. The metaphor visualisation using lightning glyphs to represent death rates posed challenges, as indicated by a lower average mean compared to the other two metaphors. Further comparison revealed that the lightning visualisation resulted in fewer correct answers than the other metaphors, suggesting that users found interpreting the frequency of lightning flashes to be more tedious and challenging than other metaphor representations. On top of this the study revealed that there exists a significant difference in cognitive demand between each standard and metaphor visualisations. When examining the means of each subtask for both standard and metaphor visualisations, it becomes apparent that metaphor visualisations impose a higher cognitive demand compared to standard visualisations. This suggests that the utilisation of natural metaphors in this context requires more time to process information for an equivalent level of understanding obtained from standard visualisations. However, for subtasks 1 and 3, utilising rainfall and sunlight as metaphor visualisations, there is not a significant difference in comparison with their respective choropleth visualisation counterparts. This indicates that the processing capabilities for both metaphors are akin to traditional choropleth maps. It is noteworthy across all subtasks that subtask B (lightning) consistently presents a higher subjective difficulty compared to the other two metaphors. The findings are consistent with how participants rate the visualisations in terms of satisfaction and confidence in the data. In Fig 13, we can see that participants express less confidence in metaphor visualisations, as the cognitive demand is slightly higher than standard visualisations, despite there being no significant difference in the correctness of information. Participants also commented that the parameterisation of the lightning metaphor was difficult to process and took a lot more time than other metaphors. This aligns with Würfer et al, 2015 proposition that cognitive load increases when parameters within metaphors use trend parameterisation (such as the frequency of lightning flashes).

Information Processing for Multivariate COVID-19 Data

The representation of multivariate COVID-19 data through a combination of standard and metaphor visualisations demonstrates a substantial difference, highlighting the impact of visualisation choice on the depth of understanding thus proving our hypothesis (H2). However, this result contradicts the findings from hypothesis H1, where the type of visualisation has no significant effect over the level of understanding univariate data. This suggests that a learning curve or prior understanding of visualisations acquired from Assignment A contribute to an enhanced perceived understanding. Examining the means of both Combined Visualisations reveals that the combined standard visualisation yields more correct answers than the metaphor visualisation. Further comparison over the correctness of answers for Question 1-3 reveal similar results. The consistency in the questionnaire format for both assignments (A and B) can be identified as the reason for this, as it allows individuals to become familiar with the task. Considering the number of correct answers for the overall assessment question (Q4) in Fig 15, it becomes apparent that the combined metaphor visualisation yields results similar to the standard visualisation for 4b (overall status of Infection Rates). However, for 4a (overall status of Death Rates), the use of pattern maps enhances understanding more effectively than the lightning metaphor. This implies that participants comprehend the rainfall metaphor even better than the standard choropleth map. Due to the limited dataset, a definitive assessment cannot be made. In contrast, the lightning metaphor proves challenging for participants, even with a learning curve for analysing death rates, where participants easily understand the pattern maps that lack an additional dimension of time (in frequent lightning flashes), which is a parameter for the lightning metaphor. To understand the subjective difficulty of participants when exposed to both multivariate and univariate visualisations, the study suggests that users can effectively handle multivariate data meaning not much significant difference in cognitive demand. Another factor to consider when looking into the subjective difficulty is the usage of layer selection in Fig 16, which most of the participants find useful in answering the task questionnaire in visualising multivariate data. Since we cannot estimate the usage of these layer selections for each question, participants gave similar results in terms of usage for both visualisations. This can aid in understanding the multivariate data tipping the significance scale. Further comparison reveals that the cognitive demand for information processing is lower for each individual standard visualisation compared to the combined standard visualisation. Suggesting that standard visualisation techniques must look into a more cohesive design. Conversely, in the case of metaphor visualisations, the average cognitive demand for each individual metaphor visualisation is higher than that of the combined metaphor visualisation. This makes the design of metaphors cohesive for viewers aiding in understanding multiple variables at once aligned with Lakeoff et al, 2003. So, metaphors have the edge over standard visualisations when careful considerations are met regarding design. In terms of readability, the study revealed that the readability was dependent on the type of visualisations. The findings suggest that combined standard visualisation outperforms its metaphor visualisations in terms of comprehending multivariate COVID-19 data. To understand the relationship between subjective difficulty and readability of participants, we looked into the spearman correlation coefficient that implies a positive relationship, indicating that higher cognitive demand correlates with increased difficulty when reading visualisations. Hence, we can say that the outcome is influenced by the increased cognitive demand imposed by metaphors during information processing which affects the preference of participants in fig 17 since 73.3% of the participants preferred combined standard visualisations even though their correctness of information is similar.

8. Conclusion

In this study, we undertook an extensive user analysis to examine the information processing of epidemiological disease like COVID-19 by incorporating natural metaphors in data representation. The findings offer a quantitative and qualitative assessment of both the difficulty of tasks and the variations in representation when employing this technique. Contrary to previous research that highlights metaphors in information visualisation, our research suggests that employing natural phenomena, like weather where we employed trend parameterisation like duration of lightning flashes and frequency of rainfall that mirrors the real world, may not necessarily influence information processing. This discrepancy could be attributed to the smaller participant size and individuals who are not yet familiar with the concept. Particularly in the medical field, there is a scarcity of empirical studies utilising such natural phenomena for information representation. Nonetheless, the research suggests that higher cognitive demand is required to understand the chosen weather metaphors and if the metaphors are easier to grasp such as the case in sunlight, one can expect an increase in information processing. While the use of metaphors in representing multivariate data has been extensively discussed (Ropinsky et al, 2011), the implementation of natural metaphors in this context remains limited. Our research also demonstrates that the use of natural metaphors provides a cohesive approach in representing multivariate data. Although the introduction of the chosen weather metaphors reduces cognitive demand, it's important to note that the understanding of trend parameterization does not necessarily become easier. In essence, our results suggest that participants grasp the visualisation techniques, as evidenced by the correctness of their answers in the task questionnaire. However, this understanding comes at the cost of increased cognitive demand, emphasising the intricacies introduced by cognitive metaphor characteristics. As we navigate the intricate intersection of design decisions, user performance, and metaphor incorporation in visualisations, our findings underscore the paramount importance of considering these cognitive nuances. Ultimately, our study prompts a revaluation of how we approach the integration of metaphors in visualisations, emphasising the need for thoughtful consideration of their impact on user experience and performance. To replicate the outcomes produced, you may examine the simulation dataset referenced in the paper by Abele et al (2021). The complete code for this research is accessible on: https://github.com/visualization-metaphor

9. Appendix

Assignment A - Task Questionnaire

A) Standard vs Rainfall Visualisation [measuring infection rate]

Topic	No	Question	Correct Answer	Answer Options
To find the extremity within the map	1	Please choose a district with the highest infection rate from the dropdown menu.	Standard: Esslingen Metaphor: Hamburg	(Mansfeld-Südharz | Wartburgkreis | Esslingen) (Hamburg | Uckermark | Emsland)
Explain the state of a particular district.	2	What is the infection rate of Münster? What is the infection rate of KS-München?	Standard: Low Metaphor: High	(High | Medium | Low)
Comparison Questions	3	LK-Rostock has a higher infection rate than Prignitz. Gifhorn has lower infection rate than Börde	Standard: False Metaphor: False	(True | False | Not enough information)
Mental demand	4	How demanding was the task to answer using the above visualisation?	3- point scale (Standard and Metaphor)	(Not demanding | Somewhat demanding | Very demanding)

B) Standard vs Lightning Visualisation [measuring death rate]

Topic	No	Question	Correct Answer	Answer Options
To find the extremity within the map	1	Please choose a district with the highest death rate from the dropdown menu.	Standard: Vogtlandkreis Metaphor: Koln	(KS-Leipzig | Chemnitz | Vogtlandkreis) (Koln | Kleve | Wesel)

Explain the state of a particular district	2	What is the death rate of the district Kleve? What is the death rate of the district Harz?	Standard: Low Metaphor: Low	(High | Medium | Low)
Comparison Questions	3	Compared to Gütersloh, what is the death rate of Bremen? The death rate in Potsdam is lower than that in the Region Hannover.	Standard: Similar Metaphor: True	(Higher | Similar | Lower) (True | False | Not enough information)
Mental demand	4	How demanding was the task to answer using the above visualisation?	3- point scale (Standard and Metaphor)	(Not demanding | Somewhat demanding | Very demanding)

C) Standard vs Sunlight Visualisation [measuring vaccination rate]

Topic	No	Question	Correct Answer	Answer Options
To find the extremity within the map	1	Please choose a district with the highest vaccination rate from the dropdown menu.	Standard: Roth Metaphor: Ortenaukreis	(Kleve | Roth | KS-München) (Reutlingen | Ortenaukreis | Konstanz)
Explain the state of a particular district	2	What is the vaccination rate of the district Nordwestmecklenburg? What is the vaccination rate of the district Kleve?	Standard: Medium Metaphor: Medium	(High | Medium | Low)
Comparison Questions	3	Bremen has a lower vaccination rate than Stuttgart. LK-Rostock has a higher vaccination rate than Erding.	Standard: False Metaphor: False	(True | False | Not enough information)
Mental demand	4	How demanding was the task to answer using the above visualisation?	3- point scale (Standard and Metaphor)	(Not demanding | Somewhat demanding | Very demanding)

User Confidence and Satisfaction Questionnaire

Topic	Question	Answer Format
Confidence	How confident are you in the accuracy of your responses to the task questionnaire?	5 Point Likert's Scale (Not Confident at All | Not Confident | Neutral | Confident | Very Confident)
Overall Satisfaction (for each subtask)	On a scale of 1 to 5, please rate your satisfaction with your ability to complete the subtasks using the (Standard/ Metaphor) visualisations	5 Point Likert's Scale (1 = Very Dissatisfied, 5 = Very Satisfied)

Assignment B - Task Questionnaire

Topic	No	Question	Correct Answer	Answer Options
To find the extremity within the map	1	Which district has the highest combination of infection, vaccination and death rate?	Standard: Hannover Metaphor: Berlin	(Hannover | Potsdam | Steinfurt) (Wittenberg | Uckermark | Berlin)
Explain the state of a particular district	2	What is the death rate of Recklinghausen? What is the vaccination rate of Steinburg?	Standard: High Metaphor: High	(High | Medium | Low)
Comparison Questions	3	Hannover and Hamburg have low vaccination rates. Hannover and Hamburg have similar death rates.	Standard: False Metaphor: True	(True | False | Not enough information)
Overall Condition	4a 4b	Compared to eastern districts, do the southern districts have a high death rate? What is the spatial distribution of infection rate in Germany?	Standard: No Metaphor: Concentrated	(Yes | No | Not enough information) (Concentrated | Spread out | Not enough information)
Mental demand	5	How demanding was the task to answer using the above visualisation?	3- point scale (Standard and Metaphor)	(Not demanding | Somewhat demanding | Very demanding)

User Readability Questionnaire:

Topic	Question	Answer Format
Readability	How would you rate the readability of the following Combined (Standard/ Metaphor) Visualisation?	5 Point Likert's Scale (1 = Very Difficult to Read, 5 = Very Easy to Read)
Effectiveness of Filters	Did you find the filters in the (Standard/ Metaphor) Visualisation effective in helping you understand the data better?	5 Point Likert's Scale (Not Effective | Somewhat Effective | Moderately Effective | Very Effective | Extremely Effective)
Visualisation Preference	Which of the two combined visualisations did you prefer in terms of readability?	(Combined Metaphor Visualisation | Combined Standard Visualisation | No Preference)

10. References

(Fig 1- 17) Flaticon.com: Icons has been designed using images from Flaticon.com

Abele et al, 2021: Abele D, Kuhn NJ, Koslow W, Siggel M, Klitz M, Rack K, et al. MEmilio (2021) - a high performance Modular EpideMIcs simuLatIOn software: Available from: https://github.com/DLR-SC/memilio.

Ahasan et al, 2020: Ahasan, Rakibul, Shaharier Alam, Torit Chakraborty, and Md Mahbub Hossain (2020): "Applications of GIS and Geospatial analyses in COVID-19 research: A systematic review." SocArXiv. August 31.

Beecham et al, 2021: Beecham R, Dykes J, Hama L, Lomax N (2021). On the Use of 'Glyphmaps' for Analysing the Scale and Temporal Spread of COVID-19 Reported Cases. ISPRS International Journal of Geo-Information; 10(4):213. https://doi.org/10.3390/ijgi10040213.

Benking et al, 1994: Benking, H., and Judge, A.J.N. (1994): Design Considerations for Spatial Metaphors: reflections on the evolution of viewpoint transportation systems. Position paper, ACM-ECHT Conference, Edinburgh 18-23 September 1994, (Invited Workshop: Spatial Metaphors for Information Systems). Available at http://www.uia.org/uiadocs/spatialm.htm.

Betz et al 2023: Betz, P. K., Stoll, J., Grappendorf, V., Gilg, J., Zeumer, M., Klitz, M., ... & Kühn, M. J (2023): ESID: Exploring the Design and Development of a Visual Analytics Tool for Epidemiological Emergencies.

Borgo et al, 2012: Borgo, Rita & Abdul-Rahman, Alfie & Mohamed, Farhan & Grant, Philip & Reppa, Irene & Floridi, Luciano & Chen, Min. (2012). An Empirical Study on Using Visual Embellishments in Visualisation. Visualisation and Computer Graphics, IEEE Transactions on. 18. 2759-2768. 10.1109/TVCG.2012.197.

Borgo et al, 2013: Borgo, Rita & Kehrer, Johannes & Chung, David & Maguire, Eamonn & Laramee, Robert & Hauser, Helwig & Ward, Matthew & Chen, Min. (2013). Glyph-based Visualisation: Foundations, Design Guidelines, Techniques and Applications.

Boulos et al, 2020: Boulos MNK, Geraghty EM (2020): Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: how 21st-century GIS technologies are supporting the global fight against outbreaks and epidemics.

Budd et al, 2020: Budd, Jobie, Benjamin S Miller, Erin M Manning, Vasileios Lampos, Mengdie Zhuang, Michael Edelstein, Geraint Rees, Vincent C Emery, Molly M Stevens, and Neil Keegan (2020): "Digital technologies in the public-health response to COVID-19." Nature Medicine (8): 1183-1192.

Cairo, 2013: Cairo, A. (2013): The Functional Art: An Introduction to Information Graphics and Visualisation. New Riders.

Card et al, 1988: Card S, Mack R, Kellog W (1988): Interface metaphors and user interface design. In: Hellander M (ed) Handbook of human-computer interaction. Elsevier Science Publisher, North Holland.

Cinnamon et al, 2009: Cinnamon, Jonathan, Claus Rinner, Michael D Cusimano, Sean Marshall, Tsegaye Bekele, Tony Hernandez, Richard H Glazier, and Mary L Chipman (2009): "Evaluating web-based static, animated and interactive maps for injury prevention." Geospatial Health 4 (1): 3-16.

De Leeuw, 1993: De Leeuw W.C, Van Wijk J. J: A probe for local flow field visualization. In Proc. IEEE Visualization (1993), pp. 39–45. 11, 15, 18

DIV, 2020: Deutsche Interdisziplinäre Vereinigung für Intensiv- und Notfallmedizin (DIVI). DIVI Intensiv Register Tages Report; 2020-10-13. Available from: https://www.divi.de/divi-intensivregister-tagesreport-archiv.

Few, 2009: Few, S. (2009). Now You See It: Simple Visualisation Techniques for Quantitative Analysis. Analytics Press.

Friendly, 2009: Friendly, M. (2009). Milestones in the history of thematic cartography, statistical graphics, and data visualisation. Retrieved from http://www.math.yorku.ca/SCS/Gallery/milestone/milestone.pdf.

Griffin et al, 2009: Griffin, Amy L, Alan M MacEachren, Frank Hardisty, Erik Steiner, and Bonan Li (2006): "A comparison of animated maps with static small-multiple maps for visually identifying space-time clusters." Annals of the Association of American Geographers 96 (4): 740-753.

Havre et al, 2002: Havre, S. & G., Hetzler & Whitney, Paul & T., Nowell. (2002). Themeriver: Visualising Thematic Changes in Large Document Collections. Visualisation and Computer Graphics, IEEE Transactions on. 8. 9-20. DOI: 10.1109/2945.981848.

Howell et al, 2022: Padilla, Lace & Hosseinpour, Helia & Fygenson, Racquel & Howell, Jennifer & Chunara, Rumi & Bertini, Enrico. (2022). Impact of COVID-19 forecast visualisations on pandemic risk perceptions. Scientific Reports. 12. 10.1038/s41598-022-05353-1.

Jacquez at al, 2010: Jacquez, G. M., Slotnick, M. J., Meliker, J. R., AvRuskin, G. A., Copeland, G., & Nriagu, J. O. (2010). Geographic clustering of lung cancer in Suffolk County, New York: evidence of a lung cancer epidemic among young women. Cancer Epidemiology, Biomarkers & Prevention, 19(10), 2546-2556.

Jebb et al (2021): Jebb AT, Ng V, Tay L. A Review of Key Likert Scale Development Advances: 1995-2019. Front Psychol. 2021 May 4; 12:637547. doi: 10.3389/fpsyg.2021.637547. PMID: 34017283; PMCID: PMC8129175.

Jonathan et al, 2019: Jonathan A Polonsky, Amrish Baidjoe, Zhian N Kamvar, Anne Cori, Kara Durski, W John Edmunds, Rosalind M Eggo, Sebastian Funk, Laurent Kaiser, Patrick Keating, et al (2019). Outbreak analytics: a developing data science for informing the response to emerging pathogens. Philosophical Transactions of the Royal Society B 374, 1776 (2019), 20180276. https://doi.org/10.1098/rstb.2018.027.

Kim 2017: Kim HY. Statistical notes for clinical researchers: Chi-squared test and Fisher's exact test. Restor Dent Endod. 2017 May;42(2):152-155. doi: 10.5395/rde.2017.42.2.152. Epub 2017 Mar 30. PMID: 28503482; PMCID: PMC5426219.

Koslow et al, 2022: W. Koslow, M. J. K¨uhn, S. Binder, M. Klitz, D. Abele, A. Bassermann, and M. Meyer-Hermann (2022). Appropriate relaxation of non-pharmaceutical interventions minimises the risk of a resurgence in sars-cov-2 infections in spite of the delta variant. PLoS Computational Biology, 18(5): e1010054, 2022.

Lakoff et al, 2003: Lakoff G, Johnsen M (2003) Metaphors we live by. The University of Chicago Press, London.

Lan et al, 2020: Lan, Yu & Desjardins, Michael & Hohl, Alexander & Delmelle, Eric. (2020). Geovisualisation of COVID-19: State of the Art and Opportunities. Cartographica: The

International Journal for Geographic Information and Geovisualisation. DOI: 10.3138/cart-2020-0027.

Landau et al, 2010: Landau MJ, Meier BP, Keefer LA (2010) A metaphor-enriched social cognition. Psychol Bull 136(6):1045–1067

Li et al, 2015: Li, Yi-Na & Li, Dong-Jin & Zhang, Kang. (2015). Metaphoric Transfer Effect in Information Visualisation Using Glyphs. 121-130. DOI: 10.1145/2801040.2801062.

MacEachren et al, 2000: MacEachren, Alan. (2000). Cartography and GIS: Facilitating collaboration I. Progress in Human Geography - PROG HUM GEOGR. 24. 445-456. 10.1191/030913200701540528.

McLafferty et al, 2011: McLafferty, S. L., & Wang, F. (2011). Rural reversal? Rural–urban disparities in late-stage cancer risk in Illinois. Cancer, 117(20), 4622-4631.

Pardo et al, 2020: Franch-Pardo, Iván & Napoletano, Brian & Rosete, Fernando & Billa, Lawal. (2020). Spatial analysis and GIS in the study of COVID-19. A review. Science of The Total Environment. 739. 140033. 10.1016/j.scitotenv.2020.140033.

Pearlman, 2007: Pearlman J, Rheingans P: Visualizing network security events using compound glyphs from a service-oriented perspective. In Proceedings of the Workshop on Visualization for Computer Security (2007), pp. 131–146. 17

RKI, 2021: Robert Koch-Institute. Coronavirus disease 2019 - Daily Situation Report of the Robert Koch Institute. Robert Koch-Institute; 2021. Available from: https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/ Situationsberichte/.

Ropinski et al, 2011: Ropinski, Timo & Oeltze-Jafra, Steffen & Preim, Bernhard. (2011). Visual Computing in Biology and Medicine: Survey of glyph-based visualization techniques for spatial multivariate medical data. Computers and Graphics. 35. 392-401. 10.1016/j.cag.2011.01.011.

Tufte, 2001: Tufte, E. R. (2001). The Visual Display of Quantitative Information. Graphics Press.

Wise et al, 1995: Wise, James & Thomas, James & Pennock, Kelly & Lantrip, David & Pottier, Marc & Schur, Anne & Crow, Vern. (1995). Visualising the non-Visual: Spatial Analysis and Interaction with Information from Text Documents. Proceedings of the Information Visualization Conference. 51. 51-58. 10.1109/INFVIS.1995.528686.

Würfel et al, 2015: H. Würfel, M. Trapp, D. Limberger, and J. Döllner (2015). Natural Phenomena as Metaphors for Visualisation of Trend Data in Interactive Software Maps Computer Graphics Systems Group, Hasso Plattner Institute, University of Potsdam, Germany. DOI: 10.2312/cgvc.20151246.

Zhang, 2008: Zhang J (2008): The implication of metaphors in information visualisation. In Visualisation for Information Retrieval, Zhang J., (Ed.), vol. 23. Springer, pp. 215–237. 2, 3.

Zhang et al, 2021: Yixuan Zhang, Yifan Sun, Lace Padilla, Sumit Barua, Enrico Bertini, and Andrea G Parker (2021). Mapping the Landscape of COVID-19 Crisis Visualisations. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21). Association for Computing Machinery, New York, NY, USA, Article 608, 1–23. https://doi.org/10.1145/3411764.3445381