

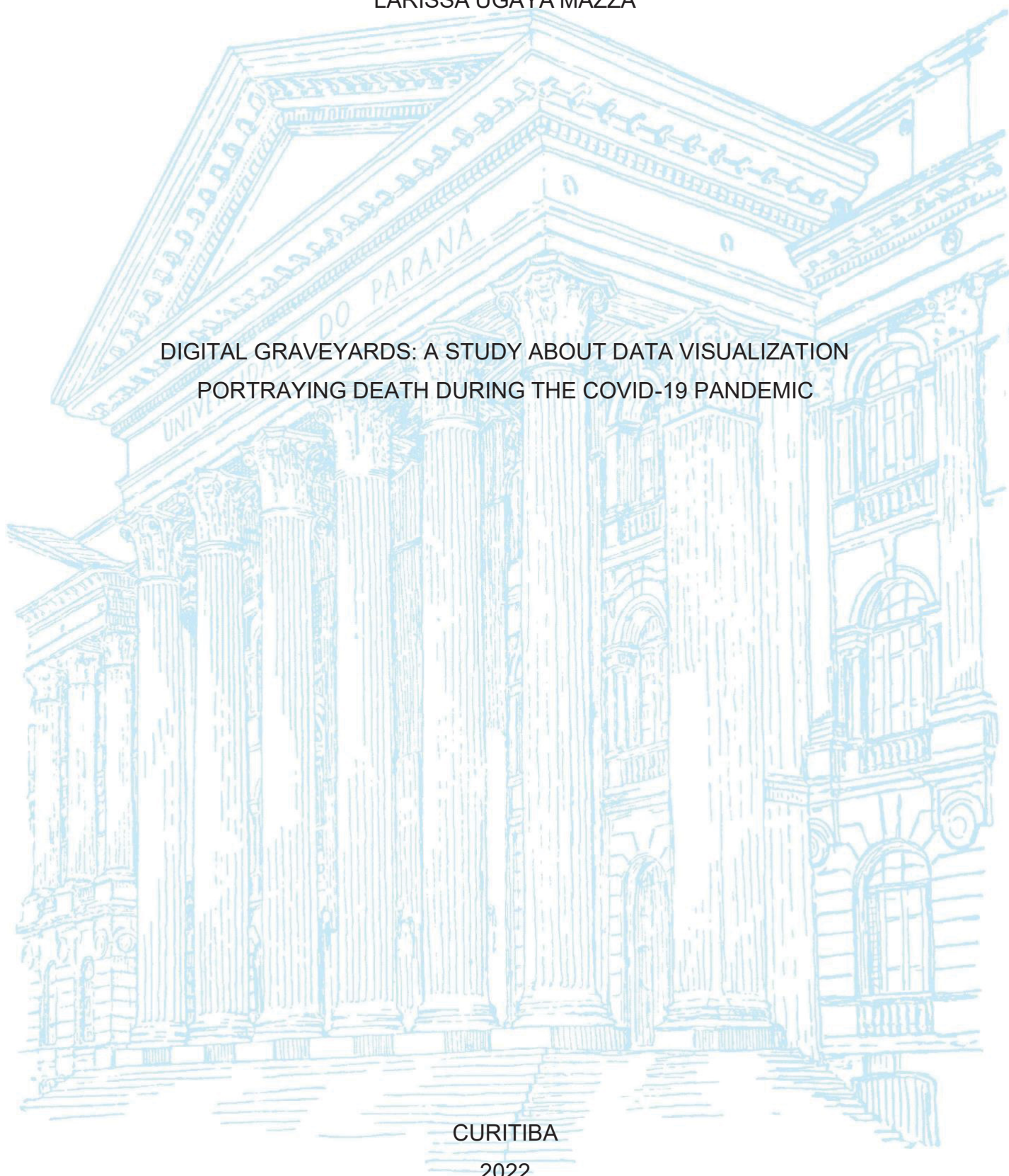
UNIVERSIDADE FEDERAL DO PARANÁ

LARISSA UGAYA MAZZA

DIGITAL GRAVEYARDS: A STUDY ABOUT DATA VISUALIZATION
PORTRAYING DEATH DURING THE COVID-19 PANDEMIC

CURITIBA

2022



LARISSA UGAYA MAZZA

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PORTRAYING DEATH DURING THE COVID-19 PANDEMIC

Dissertação apresentada ao curso de Pós-Graduação em Design, Setor de Artes, Comunicação e Design, da Universidade Federal do Paraná, como requisito parcial à obtenção do título de Mestre em Design.

Orientadora: Profa. Dra. Luciane Maria Fadel

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Assinatura Eletrônica

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Presidente da Banca Examinadora

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VIRGINIA TIRADENTES SOUTO

Avaliador Externo (UNIVERSIDADE DE BRASÍLIA)

Assinatura Eletrônica

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CARLA GALVÃO SPINILLO

Avaliador Interno (UNIVERSIDADE FEDERAL DO PARANÁ)

RUA GENERAL CARNEIRO, 460 - CURITIBA - Paraná - Brasil

CEP 80060-150 - Tel: (41) 3360-5238 - E-mail: ppgdesign@ufpr.br

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“A morte...
significa alguma coisa!”
- Thiago Guimarães

RESUMO

Com a COVID-19 as visualizações de dados tornaram-se amplamente utilizadas para divulgar o número de casos, vacinações e mortes ao público. Estas visualizações trazem dados sobre morte e infecção, informações que são sensíveis para aqueles que as leem. A apresentação de dados sensíveis pode modular o comportamento dos usuários e orientar como eles reagem às medidas de saúde. Esta pesquisa aborda como as visualizações de dados foram usadas durante a pandemia COVID-19 e como elas afetam o usuário. Assim, propõe desenvolver um framework analítico descritivo para mapear como os elementos visuais presentes na visualização de dados promovem a consciência da morte. A metodologia utilizada foi a pesquisa qualitativa, com uma fase exploratória seguida por uma fase explicativa. A exploração foi utilizada para entender como a consciência da morte se relaciona com os comportamentos relacionados à saúde e a interação com as visualizações de dados, enquanto a fase descritiva foi utilizada para coletar teorias e verificar resultados. Uma amostra de três visualizações de dados foi analisada usando um protocolo para analisar elementos visuais e como eles contribuem com o engajamento, agência e consciência da morte. Os resultados mostram que as visualizações que estão sendo usadas durante os tempos de pandemia emprestam muitos elementos de *templates*, com pouca consideração pelo que significa representar dados sensíveis nesse formato. Isto cria modos de representação que fazem sentido lógico, mas fomentam o medo e arriscam consequências negativas para os usuários.

Palavras chave: Visualização de dados. Agência. Consciência da morte. Pandemia. COVID-19. Informação sensível.

ABSTRACT

With COVID-19 data visualizations have become widely used to disseminate the number of cases, vaccinations, and deaths to the public. These visualizations carry data about death and infection, information that is sensitive to those who read them. The presentation of sensitive data can modulate users' behavior and guide how they react to health measures. This research addresses how data visualizations were used during the COVID-19 pandemic and how they affect the user. Thus, it proposes to develop a descriptive analytical framework to map how the visual elements present in data visualizations promote death awareness. The methodology used was qualitative research, with an exploratory phase followed by an explanatory phase. The exploration was used to understand how death awareness relates to health-related behaviors and interaction with data visualizations, while the descriptive phase was used to collect theories and verify results. A sample of three data visualizations was analyzed using a protocol to analyze visual elements and how they contribute to engagement, agency, and death awareness. The results show that the visualizations being used during pandemic times borrow many elements from templates, with little consideration for what it means to represent sensitive data in that format. This creates modes of representation that make logical sense, but foster fear and risk negative consequences for users.

Keywords: Data visualization. Agency. Death awareness. Pandemic. COVID-19. Sensitive information.

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LIST OF ABBREVIATIONS

AC – Annotation Chart

CDC – Centers for Disease Control and Prevention

COVID-19 – Coronavirus Disease

DA – Death Anxiety

DR – Death Reflection

DV – Data visualization

ID – Information Design

IIID – International Institute for Information Design

MR – Mortality Reminder

NLR – Narrative Literature Review

PAHO – Pan-American Health Organization

PHEIC – Public Health Emergency of International Concern

PTG – Post-Traumatic Growth

SLR – Systematic Literature Review

SSCE – Semantic, Syntactic, Classification, and Elements of engagement

TMHM – Terror Management Health Model

TMT – Terror Management Theory

WHO – World Health Organization

WWII – World War II

JHU – John Hopkins University

UTFPR – Universidade Tecnológica do Paraná

DIKW – Data, Information, Knowledge, Wisdom

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1 INTRODUCTION

1.1 COVID-19 PANDEMIC

In December 2019, the World Health Organization (WHO) received the first notice of the novel SARS-CoV-2 spreading in Wuhan, China. The virus was a new strand of coronavirus, previously unable to infect humans. According to the Pan-American Health Organization (PAHO), the coronavirus is an ordinary family of viruses, of which six were previously identified to be contagious for humans, now seven counting SARS-CoV-2. This new disease was COVID-19 (WORLD HEALTH ORGANIZATION, 2020).

Faced with this new threat, on January 30th, 2020, the World Health Organization declared a Public Health Emergency of International Concern (PHEIC), which is a formal declaration given by WHO during extraordinary conditions when an event is considered to constitute health risks through international spread, which can potentially require a global response (PAHO, 2020). This scenario made COVID-19 the sixth time in history where such a response was needed, the last one being the Ebola outbreak in May 2018.

In March 2020, WHO officially characterized COVID-19 as a pandemic, the first in many years. According to the Centers for Disease Control and Prevention (CDC, 2009), the last recorded pandemic before COVID-19 was the H1N1 outbreak in 2009.

1.2 CONTEXT AND PROBLEM

Amidst all the death that comes from a pandemic, there has been a surge in the use of data visualization (DV) to track infections, hospitalizations, and deaths (COOLEY, 2020; GREEN, 2020). Data visualization (DV) can be described as “the reduction and spatial representation of datasets in such a way as to make them more intelligible than in their pre-visualization, tabular format” (HEPWORTH, 2016, p. 8).

Data visualizations act as cognitive assistance for interactors¹ to efficiently interpret data (BRAGA; PONTES E SILVA; SOUTO, 2020). They have always been used to communicate information, still, COVID-19 content is sensitive data and should, thus, be treated with humanity (COOLEY, 2020).

The speed with which the pandemic progresses imposes DV production to be fast and efficient, making it subjective to errors (GREEN, 2020). A few problems arise because of automatically updated data trying to track a global event in real-time. Issues like missing or suppressed data, regional inconsistencies, and dynamic data availability make inaccurate data available for public consumption immediately (GREEN, 2020).

Many websites were created to monitor data about the pandemic and present it graphically. The first was a dashboard by John Hopkins University (JHU), presenting information about contamination and death (COMBA, 2020). Others soon followed, some official (e.g., *Coronavírus Brasil*, <https://covid.saude.gov.br/>), others connected to academic institutions (e.g., GYRO 4life, <https://4life.gyro.ct.utfpr.edu.br/>) and even private ones (e.g., dados transparentes, <https://www.dadostransparentes.com.br/>). Major organizations began mobilizing to create dashboards, such as WHO, CDC, PAHO, the New York Times, the Washington Post, and more.

For the most part, the data visualizations (DV) are what Cooley (2020) calls tracking dashboards, which are DV focused on monitoring the progression of the pandemic. The author highlights their importance and urges data designers to create more visualizations that focuses on emotion, shifting from complete accuracy into the experience of being touched by a story. The author argues that people will become more engaged and motivated to enact change this way.

Data visualization can benefit the user, allowing them to easily see impossible or complicated data (RODRÍGUEZ; NUNES; DEVEZAS, 2015). It is a resource that takes advantage of human cognitive abilities to foster understanding on a level that raw data cannot provide (GOMES; PIMENTA; SCHNEIDER, 2019). Using images to convey information can assist in

¹ This project will use the word **interactor** to mean an interactor to emphasize the importance of the interaction between person and data visualization.

understanding since they tend to be less ambiguous than their written counterparts (AINSWORTH, 2008). Data visualizations often employ numbers to aid objectivity, management, and governance, making the 'emotional distance' in DV significant for impartiality (GRAY, 2020).

However, such impartiality risks transforming data about delicate topics (such as death) into numbers to be managed, taking the emotion out of very naturally emotional data (HEPWORTH, 2016). When presenting large quantities of data to a person, there is the possibility that the overwhelming amount of information will lead to a less emotional response (COOLEY, 2020). As information increases, people lose the notion that a single action can make a difference and become less engaged (COOLEY, 2020).

However, not all graphs are effective for all situations, and the designer must carefully choose the best way to represent a specific type of data for the intended purpose (TVERSKY; MORRISON; BETRANCOURT, 2002). Since the designer is responsible for so many choices in representation, it falls upon them to choose graphic elements to convey the message desired. Data visualization privileges particular worldviews and can carry ideologies and political statements. In this sense, DV creates meaning, signs, and values and legitimizes ideas of a specific group (NÆRLAND, 2020).

Data visualization is riddled with inequalities and creates a power imbalance that results from not everyone understanding it at the same level (PINNEY, 2020). Exploring DV can be complicated when one is not used to the language. This may, unintentionally or not, cause the interactor to misinterpret the meaning of the data (TØNNESSEN, 2020).

The way information is presented is not incidental, and neither are the conclusions the interactors draw from it (EISNER, 1997). It is impossible to make genuinely neutral visualization (VIÉGAS; WATTENBERG, 2007). Instead of making unbiased representations, designers should aspire to create visualizations for an intended purpose and choose graphical elements to support this goal (VIÉGAS; WATTENBERG, 2007).

In the case of the current pandemic, Doan (2020) has discussed how COVID-19 visualizations have already been used to mislead users. Data designers have the power to alter a representation to persuade or deceive the

interactor and effectively change their perspective (PANDEY *et al.*, 2015). The ones who collect and decide what to do with data are in a position of power over those with their data collected, whether they realize it or not (PINNEY, 2020).

On the other hand, data visualizations can also assist people in making informed choices and taking social and political action (NÆRLAND, 2020). Therefore, data visualizations being used during the COVID-19 pandemic should seek to inform the interactors to support decisions about their health and safety. In addition, this information should seek to ascertain citizens' rights by allowing interactors to recognize themselves and their situation in the visualization (NÆRLAND, 2020), giving them power.

This recognition happens when the interactors understand the language of DV, allowing them to become agents for their own lives. They can reflect upon the DV and contextualize it in a way that becomes meaningful (TØNNESSEN, 2020). This involvement with the media is called agency. Murray (1997, p. 126) defines agency as "the satisfying power to take meaningful action and see the results of our decisions and choices." More than just action, agency is how one perceives their possibility to act (EICHNER, 2014).

1.3 THEORETICAL FOUNDATION

1.3.1 Agency

Eichner (2014) and Murray (1997) explain agency as the possibility to act and see action shape the world. The former divided agency into personal, creative, and collective. However, just as important as the definitions given by Eichner and Murray is the definition of agency as the commitment to meaning (TANENBAUM; TANENBAUM, 2009). The authors discuss how agency is more than just choice; it is committing to the world one is inserted into and acting according to the meaning it dictates.

In DV, the three definitions are valid, as they provide ways to glean insights into how a DV can shape the way interactors will engage with the world, make choices, and assert themselves. Through the lenses of agency,

the concept that makes all human perceive themselves as actors in their own lives, it becomes possible to assess how DV impacts human behavior.

However, COVID-19 data visualization is about sickness and death. The graphs and tables often deal with contagion numbers, casualties, and infections, all of which carry a sense of loss of human life (see *Coronavírus Brasil*, <https://covid.saude.gov.br/>, GYRO 4life, <https://4life.gyro.ct.utfpr.edu.br/>, and *dados transparentes*, <https://www.dadostransparentes.com.br/>).

Interacting with death is always a complicated process. Sontag (1978) describes this in her book, where she outlines how different diseases are treated. Despite having the same connotation of death, the author shows that various conditions were historically given different societal meanings. She discusses tuberculosis, which was considered tragically beautiful, in contrast with cancer, a deadly alien. The same message of death was given different meanings by a society based on how it was perceived and represented (SONTAG, 1978).

1.3.2 Terror Management Theory

There is always a risk that representing death can turn the loss of human life into mere administrative numbers (HEPWORTH, 2016). As for the human perspective, Greenberg and Arndt (2012) pose the Terror Management Theory (TMT), which arises from the internal conflict caused by humans' cognitive ability to understand their mortality and self-preservation instincts. The clash between these two systems causes an ever-present feeling of terror known as death anxiety (GRANT; WADE-BENZONI, 2009).

To manage this type of anxiety, people adopt self-made systems based on cultural worldview, self-esteem, and close relationships (GREENBERG; ARNDT, 2012; PYSZCZYNSKI *et al.*, 2020).

This system controls existential terror by providing a person with the comforting message that they live a meaningful life. Because of the current state of the world, managing TMT is far more complex, as the anxiety buffering systems have been cut off by healthcare guidelines (PYSZCZYNSKI *et al.*, 2020).

However, a large body of literature suggests that healthcare guidelines are not always followed, even when they provide safety (GREENBERG; ARNDT, 2012). Instead, the anxiety buffering system removes focus and concentrates elsewhere when reminded of death. When the focus of death has been removed from consciousness and passed onto sub-consciousness, people tend to favor choices that will boost their worldviews and self-esteem, not necessarily what is best for their health and safety and that of others (GOLDENBERG; ARNDT, 2008).

To have these responses, people need to be subjected to mortality reminders (MR) and become aware of their mortality (ROSENBLATT *et al.*, 1989). Awareness has many different connotations, but generally, it happens when someone can conceive a notion (SCHIPPER, 2014).

Chalmers (1996, p. 225) defines awareness as "the state wherein some information is accessible for a verbal report and the deliberate control of behavior." More specifically, awareness is the possession of information when that information directly impacts behavior (CHALMERS, 1996).

1.3.3 Research question

Data visualizations have been a primary source of how people are informed about death during the COVID-19 pandemic. It becomes essential to assess how data visualization fosters awareness in COVID-19 death representations. These visualizations, as any visualization, can infer emotions and contain hidden meanings, other than just purely informing the interactor (VIÉGAS; WATTENBERG, 2007). They present the past and make projections for the future by actively playing a role in how the future shapes up (RETTBERG, 2020) and function as mortality cues, reminding people of the constant threat of death (GRANT; WADE-BENZONI, 2009). Thus, visual representations might impact the awareness of death and affect how people process it.

From this context, the research question was: **how might data visualization foster awareness in COVID-19 death representations?**

Two arguments are considered when answering this question. The first is that the design of DV can evoke agency, as defended by Murray and

Eichner. Getting involved with a DV through agency can make the interactors interpret the message as meaningful and relevant to their lives, thus becoming motivated to protect their health and those around them. When this happens, the interactors might become aware of their mortality, which will modulate how they respond to the healthcare guidelines.

The second argument is that identifying the design elements that contribute to agency and act as mortality reminders can contribute to the design processes for creating DV for sensitive information. Both arguments lead to the objectives of this dissertation, which follow.

1.2 OBJECTIVES

1.2.1 Main objective

Develop a descriptive analytic framework for mapping out how the visual elements present in data visualization foster death awareness.

1.2.2 Secondary objectives

To achieve this goal, three secondary objectives were formulated:

- Establish how designers use graphic elements to create data visualizations;
- Map out how data visualizations have been used to represent death in the context of the COVID-19 pandemic;
- Trace connections between the modes of death representation in the data visualizations and agency;

1.3 JUSTIFICATION

Data visualizations are being shown daily to the broader public while re-contextualizing actual losses and grief as just numbers on the screen (COOLEY, 2020; HEPWORTH, 2016). There is much death portrayed in media, yet the way it is delivered is not always compatible with the severity of

the content (COOLEY, 2020). The ramifications of presenting sensitive data as less emotional information affect how people respond to healthcare guidelines (COOLEY, 2020; GOLDENBERG; ARNDT, 2008; GREENBERG; ARNDT, 2012; HEPWORTH, 2016; PYSZCZYNSKI *et al.*, 2020), so designers must understand how their design choices can modulate interactor behavior.

There is insufficient research reporting on how designers can visualize data to foster healthy behavior, especially when designing DV dealing with sensitive topics like death. Research on data visualization has focused on ways to improve DV understanding (GRIMALDI; FOKKINGA; OCNARESCU, 2013; HORNBAEK; OULASVIRTA, 2017; KELLEHER; WAGENER, 2011; OTTEN; CHENG; DREWNOWSKI, 2015; RODRÍGUEZ; NUNES; DEVEZAS, 2015; STEPHENS, 2015), the role of DV in persuading the interactor (EISNER, 1997; EVERGREEN; METZNER, 2013; PANDEY *et al.*, 2015, 2014), and the responsibility of the designer to be ethical (HEPWORTH, 2016; MACPHERSON-KRUTSKY, 2020). However, there is little research on better design representations when tackling sensitive content.

The social relevance of this research lies in helping designers better understand how design elements impact interactor behavior and influence how interactors act regarding their health and that of others.

The academic relevance was established after the state of the art was observed through a literature review. A knowledge gap was found in how data visualization handles informing people about the sensitive topic of mortality. This research contributes to more transparent and horizontal communication between data professionals and ordinary folks.

2 DATA VISUALIZATION

Data visualization (DV) can be described as “the reduction and spatial representation of datasets in such a way as to make them more intelligible than in their pre-visualization, tabular format” (HEPWORTH, 2016, p. 8).

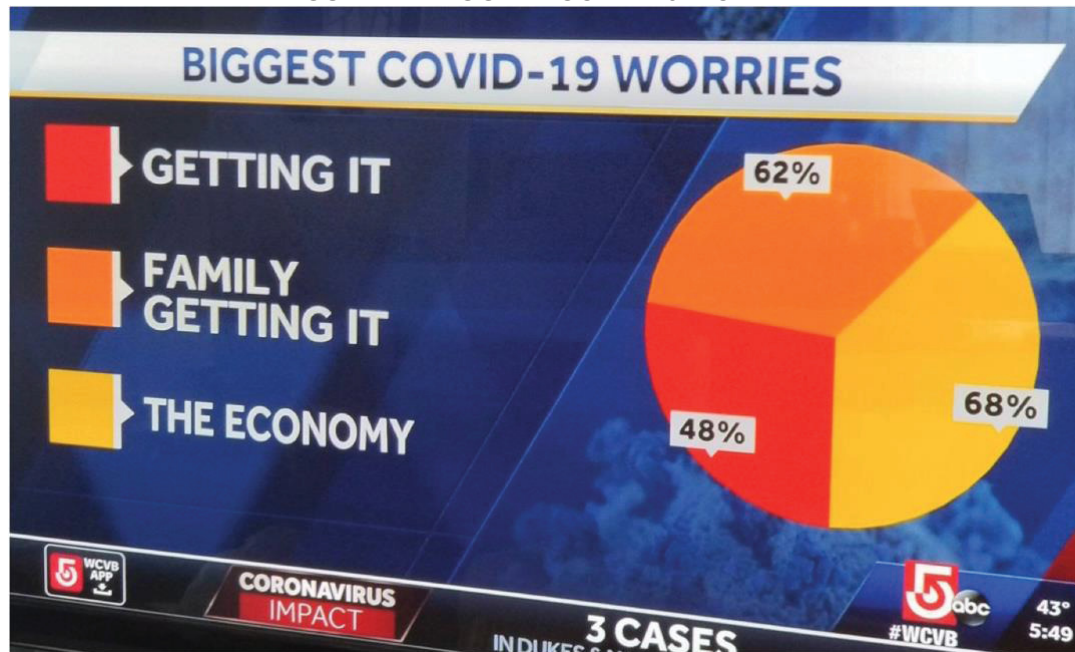
Currently, more data is generated, collected, stored, and made accessible than ever before (KENNEDY; ENGBRETSSEN, 2020). They take on the critical role of providing insights into patterns and trends that could otherwise go unnoticed (KENNEDY; ENGBRETSSEN, 2020). Therefore, DV becomes an essential tool to bridge the gap between those producing and consuming information (OTTEN; CHENG; DREWNOWSKI, 2015).

2.1 DATA VISUALIZATION, PROMISES AND PITFALLS

One of the promises of DV is helping people visualize impossible or difficult concepts, as well as large quantities of data or abstract notions (CABITZA *et al.*, 2016; RODRÍGUEZ; NUNES; DEVEZAS, 2015). Rettberg (2020) argues that data is an excellent way to infer correlation but not causality. Numbers can predict human behavior quite effectively but fail in understanding motivation for said behavior (RETTBERG, 2020).

Recently, data visualization has been used in multiple sectors. At best, it can convey complex facts and allow for patterns and trend findings. At worst, it can confuse or manipulate interactors (KENNEDY; ENGBRETSSEN, 2020). FIGURE 1 shows one example of confusingly presented data, where ABC showed a pie chart to showcase the biggest COVID-19 concerns. The chart has percentages that added 178% instead of 100%. FIGURE 1 is an example of a bar chart being replaced by a pie chart, resulting in a confusing and vague DV.

FIGURE 1 – BIGGEST COVID-19 WORRIES

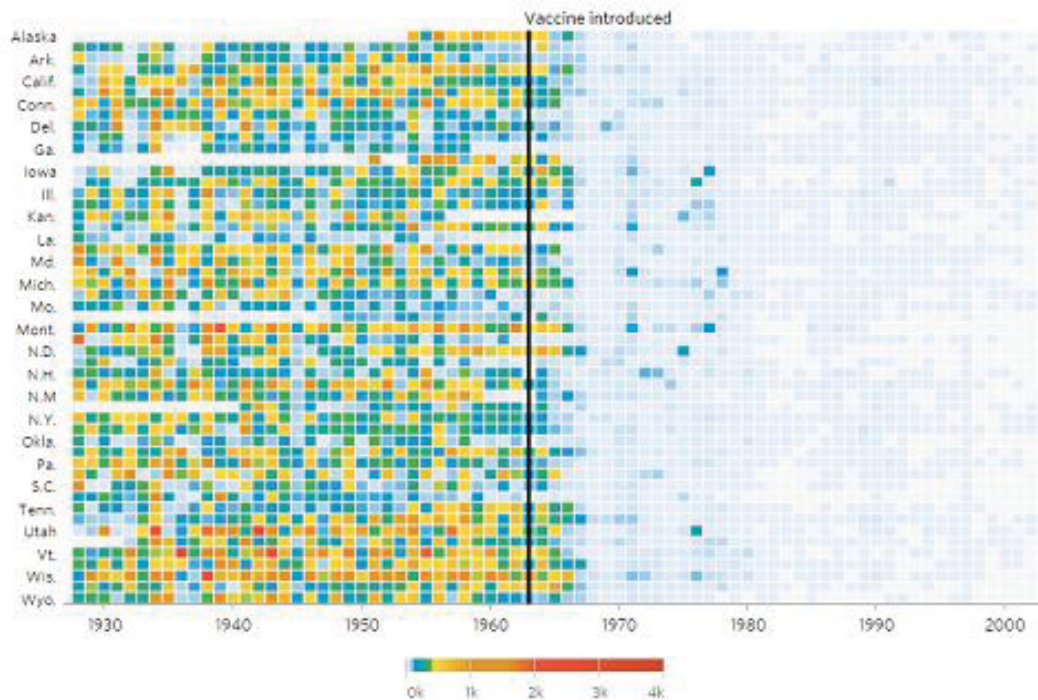


SOURCE: Junk Charts. Available on:
https://junkcharts.typepad.com/junk_charts/pie_chart/. Accessed: 31 May. 2021.

When DV is used well, the result can allow interactors to grasp messages quickly through simplification (KENNEDY; ENGEBRETSEN, 2020). One example is the DV made by Tynan DeBold and Dov Friedman of the Wall Street Journal, which showed the impacts of vaccines throughout the years. The authors conveyed that measles significantly decreased with vaccines (FIGURE 2).

However, confusing or assisting interactors is not the only impact DV can have. Nærland (2020) discusses the role data visualization plays on citizenship. Data visualizations can engage people and present them with the information they connect with, thus increasing their engagement with the social and political structures they are inserted into. They serve as a support for citizens to make informed decisions. On the other hand, they can manipulate and misinform to a level that destroys one's abilities to decide (NÆRLAND, 2020).

FIGURE 2 – VISUALIZING THE IMPACT OF VACCINES, MEASLES

Measles

SOURCE: Center for Data Innovation. Available on:
<https://datainnovation.org/2015/02/visualizing-the-impact-of-vaccines/>. Accessed: 31 May. 2021.

Transforming data into visualizations is not a new concept, dating from early map-making times in the 19th century. However, data has gained popularity and social relevance recently, as it becomes increasingly valued and shapes the way one perceives the world and makes decisions (KENNEDY; ENGBRETSSEN, 2020).

Differently than simply presenting information, data visualization offers a space for the interactor to explore and interpret the meanings of the information for themselves (RODRÍGUEZ; NUNES; DEVEZAS, 2015).

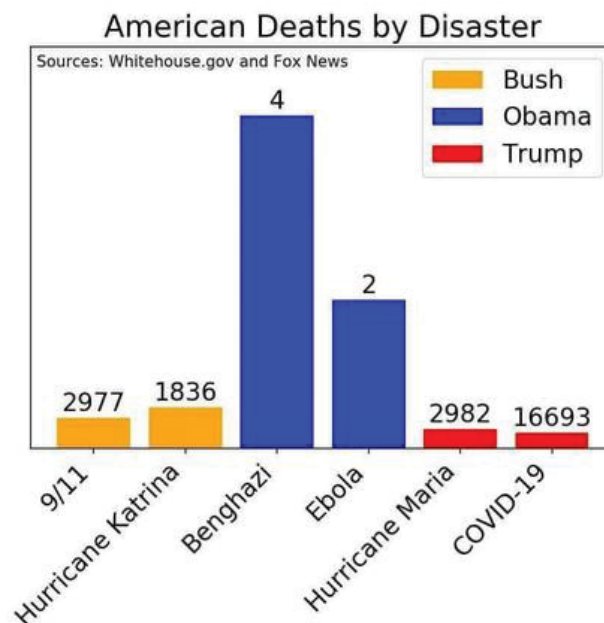
Although often DV does, it is not necessarily made to simplify data, but to provide cognitive assistance and, in some instances, translate information to the interactor (BRAGA; PONTES E SILVA; SOUTO, 2020). Therefore, its primary purpose is to translate visual cues that present evidence and prioritize specific meanings (BRAGA; PONTES E SILVA; SOUTO, 2020).

Additionally, data visualization facilitates interactor understanding and promotes persuasion (KENNEDY; ENGBRETSSEN, 2020). Indeed, DV has a

history of being closely tied with politics, shaping minds and opinions often at a subconscious level (HEPWORTH, 2016). They can prioritize the ideologies of the people producing it and often instate meanings, signs, and values on the interactors (NÆRLAND, 2020).

For example, the graph in FIGURE 3, published by Fox News, shows a bar chart detailing deaths by a disaster in the USA, comparing them by which president was in office at the time. The bars, however, are not proportional to the numbers they represent, so much that one might say this graph is trying to further the narrative that under President Obama, there were more fatalities than when Bush or Trump was in office.

FIGURE 3 – AMERICAN DEATHS BY DISASTER.



SOURCE: Reddit r/dataisugly. Available on: https://www.reddit.com/r/PoliticalHumor/comments/fz1tos/american_deaths_by_disaster/. Accessed: 31 May. 2021.

People rely on DV constantly, from decision-making to communication, making it essential for designers to understand their responsibility in maintaining ethics, especially considering the ease of using visualizations and statistics (HEPWORTH, 2016; MACPHERSON-KRUTSKY, 2020). Data visualizations not only can be tools for predicting the future, but by claiming it, they are also shaping the way the future will take form, and designers should be mindful of this power (RETTBERG, 2020).

The use of DV seems to come with the connotation of absolute truth. The simple presence of visual data is enough to compel people, regardless of the validity of the information (RETTBERG, 2020). Much more than raw data, DV uses color, shape, and composition to engage the users. There is an element of visual pleasure absent from other forms of data presentation, an aesthetically pleasing feature to the eye (KENNEDY; ENGBRETSSEN, 2020). As Hepworth (2016, p. 7) puts it, "Seeing is believing because seeing is seduction." Data visualization, much more than other types of communication, presents reality as predictable and understandable and thus, enticing (RETTBERG, 2020).

However, data by itself does not carry weight or meaning. Instead, they demand designers to translate their significance and articulate them into a story, which will seek to affect people in some specific way (BRAGA; PONTES E SILVA; SOUTO, 2020; VIÉGAS; WATTENBERG, 2007). Data does not exist in a vacuum, and people present it as part of an argument (NÆERLAND, 2020).

2.2 DATA, INFORMATION, AND KNOWLEDGE

The word data dates back to the XVII century, and it comes from the Latin word *datum*, which means a single piece of information (SEMELER; PINTO, 2019). The Oxford dictionary defines data as "facts or information, especially when examined and used to find out things or to make decisions" (DATA, 2021). However, the definition of data is not yet set, with many authors proposing different interpretations (HJØRLAND, 2018).

For this research, two definitions of data will be used: Semeler and Pinto (2019) and Gomes et al. (2019). Data here will be defined as "objects created digitally or converted into digital, that can be used to generate information and knowledge" (SEMELER; PINTO, 2019, p. 115) and "the register of the attribute of an entity, object or phenomenon" (GOMES; PIMENTA; SCHNEIDER, 2019, p. 5).

When one registers something, they transform it into a document through organization and documentation to be filed and recuperated following a set of rules. For example, when organizing files into folders, a system

dictates where each file has to go to be easily retrieved in the future (GOMES; PIMENTA; SCHNEIDER, 2019).

With these definitions, data becomes the basis of the DIWK hierarchy (Data, Information, Knowledge, and Wisdom), a process where "information is understood as processed or interpreted data, knowledge as processed or interpreted information, and wisdom as interpreted knowledge." (HJØRLAND, 2018, p. 6).

Data by itself is meaningless, simply a collection of symbols resulting from an inquiry, and to become meaningful, this data needs to be organized and transformed into information, which is the purpose of the field of Information Design (ID) (KAZMIERCZAK, 2003; OLIVEIRA *et al.*, 2013). This field looks to simplify complicated information to make it more accessible (OLIVEIRA *et al.*, 2013).

The International Institute for Information Design (IIID) defines Information Design as "the defining, planning, and shaping of the contents of a message and the environments in which it is presented, to satisfy the information needs of the intended recipients" (DESIGN, 2021). Based on this, it is possible to infer that Information Design governs the process of producing DV, as they both seek to transform data into information.

2.3 DATA VISUALIZATION AS STORYTELLING

The understanding of DV goes beyond what the surface presents. To engage with data visualizations in a meaningful way, it is essential to consider the context they are inserted in and not just what they say (ARCHER; NOAKES, 2020; GEE, 2003).

For example, Pandey *et al.* (2015) describe how data visualization can be altered, not to lie, but prioritize specific meanings and willfully make interactors misinterpret a message. For example, Hepworth (2016) presents a graph from a USA drone attack where the designers chose to name casualties as 'enemy kills' despite being unable to identify if the people killed were civilians, children, or soldiers. She argues that language and the dismissal of human life created a narrative that antagonizes the casualties and painted the USA as heroes of the story.

Because of the persuasive nature of DV, it becomes crucial to take a moment to assess what message DV is trying to send, what is the source of information, and how it is being presented (MACPHERSON-KRUTSKY, 2020), so it becomes easier to identify representations like the one Hepworth highlighted, which intentionally reduced large scales of human life loss to mere administrative numbers (HEPWORTH, 2016). This presents another facet of DV, which strives for telling stories instead of ultimate neutrality.

Indeed, many authors argue that data visualizations should not be neutral but constructed to further a message or even tell a story (EISNER, 1997; VIÉGAS; WATTENBERG, 2007). Considering that it is impossible to make a DV devoid of bias, designers can strive to use them as tools for telling a story (BRAGA; PONTES E SILVA; SOUTO, 2020).

Stories are an ever-present and deeply rooted piece of society. They have many purposes, such as informing, recording, explaining, persuading, understanding and entertaining (WEBER, 2020). Stories help to make sense of the world and evoke emotions (WEBER, 2020). Cooley (2020) highlights that DV had better results when looking for empathy and engagement from the interactors when it focused on storytelling and the emotional impact of single stories, instead of presenting the whole picture.

In a DV, four narrative elements are most commonly present and provide the interactor with storytelling (WEBER, 2020): narrators, sequentially, temporal dimensions, and tellability. Pronouns used in the text, voice narration, comments that infer opinion (ex. the numbers increase dramatically), and animation (which implies someone choosing the order the information is shown) create a narrator.

According to Ryan (2007), sequentiality means a sequence of structured events in which an event correlates and triggers another. The events must be facts within the story, not hypotheses or instructions, and must be completed (news about an ongoing event does not qualify).

Sequentiality in DV might assume many forms. One of them is through scroll telling, where scrolling is combined with the zoom in/out feature to make up a story. This can happen with input from the interactor or not. For example, the scroll telling in animations is entirely under the designers'

control, unlike in interactive DV, when the interactor controls the transitions (WEBER, 2020).

However, not all DV tells a story, some of them – such as pie charts and treemaps – represent facts (RODRÍGUEZ; NUNES; DEVEZAS, 2015). On the other hand, line graphs present changes over time and tell a story, as they have sequentiality (RODRÍGUEZ; NUNES; DEVEZAS, 2015; WEBER, 2020). Another element of narratives is tellability (RYAN, 2007), or how meaningful a story is to the listener. Tellability becomes present in a DV if the interactors connect to the message and take it as significant for their lives. Meaning making, in general, and applied to data visualization, comes from the interactor's context and the visualization (ARCHER; NOAKES, 2020; WEBER, 2020).

2.4 MEANING MAKING

Meaning is defined as the “cognitive categories that make up one’s view of reality and with which actions are defined” (KRAUSS, 2005, p.762) and is one of the most fundamental parts of being human. Because they are so powerful, the meaning becomes the underlying motivation behind actions, feelings, thoughts, and behaviors (KRAUSS, 2005).

In the field of data design, meaning can be defined as a “thought induced in the receiver, which is originated by the contact with the design” (KAZMIERCZAK, 2003, p. 47). Meaning does not come from the data itself but the design—the focus shifts from designing objects to designing thoughts or inferences (KAZMIERCZAK, 2003).

Meaning is the product of a process between three agents: the designer, design, and interactor (KAZMIERCZAK, 2003). It starts at the first stage as the intended meaning defined by the designer. Once at the interactor stage, the meaning is redefined to the meaning/content of the design. The receiver, however, is not in complete control of the meaning as the design and designer influence how the meaning will most likely be formed (KAZMIERCZAK, 2003).

Additionally, meaning making refers less to the event than what changes happen to a person’s idea of self and internal beliefs after the event

has occurred (PARK, 2010). The consensus on meaning-making seems to come in the form of a set of essential tenets (PARK, 2010):

- a) People have orienting systems (systems that consist of individual beliefs, goals, and subjective feelings) that provide motivation and cognitive frameworks for people to use when interpreting experiences;
- b) When encountering situations that put that orientation system at-risk, people assess the situations and assign meanings to them;
- c) The extent that that meaning disagrees with the orientation system is the extent someone will experience distress;
- d) This distress initiates meaning-making;
- e) Through meaning-making, people try to reduce the discrepancy between their orientating system and the meaning ascribed to the situation;
- f) When this process is successful, it improves adjustment to a stressful event.

Meaning making can be deliberate (coping activities) or automatic/unconscious (PARK, 2010). For the discrepancy between the orientating system and appraising meaning to be resolved, one of them (or both) must change. Accommodation happens when the orientating system changes to fit in the appraising meaning. Assimilation is the opposite process (PARK, 2010).

A negative side of meaning-making is the possibility of being more distressed than before. This happens when a person ruminates on making meaning to no avail, a similar process to attempting to reach a locked away goal, which causes frustration (PARK, 2010).

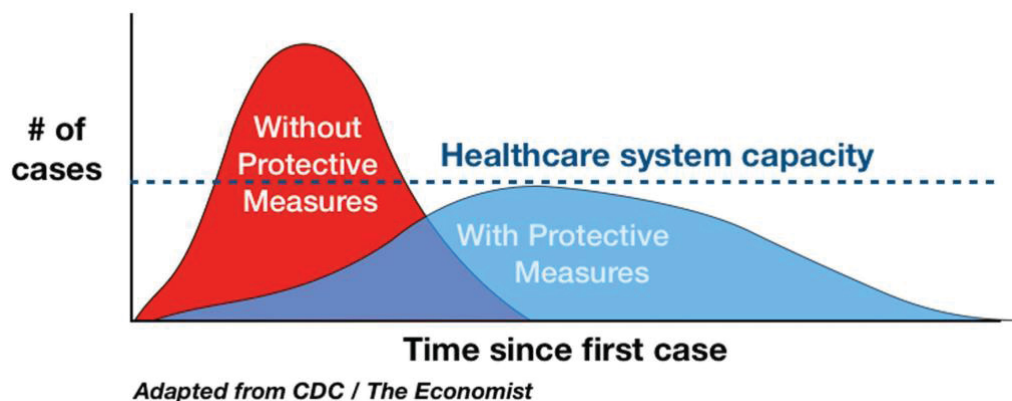
Meaning thus becomes an essential part of the narrative within DV. Despite not all data visualizations being considered narratives, they all intend to pass messages. It is impossible to make a neutral representation, either by the interference of designer bias, or data manipulation, whether intentional or not (BRESCHIANI; EPPLER, 2015; DOAN, 2020; HEPWORTH, 2016; VIÉGAS; WATTENBERG, 2007).

2.5 SIMPLIFICATION AND DESIGNER BIAS

One of the fundamental characteristics of DV is simplification and synthesis (RODRÍGUEZ; NUNES; DEVEZAS, 2015), which requires the designer to judge what information is necessary and which can be removed. This process is heavily influenced by the designer's beliefs and can cause impartial representations. The visualization creators judge what data is relevant enough to be maintained and which piece of information can be removed (BRAGA; PONTES E SILVA; SOUTO, 2020).

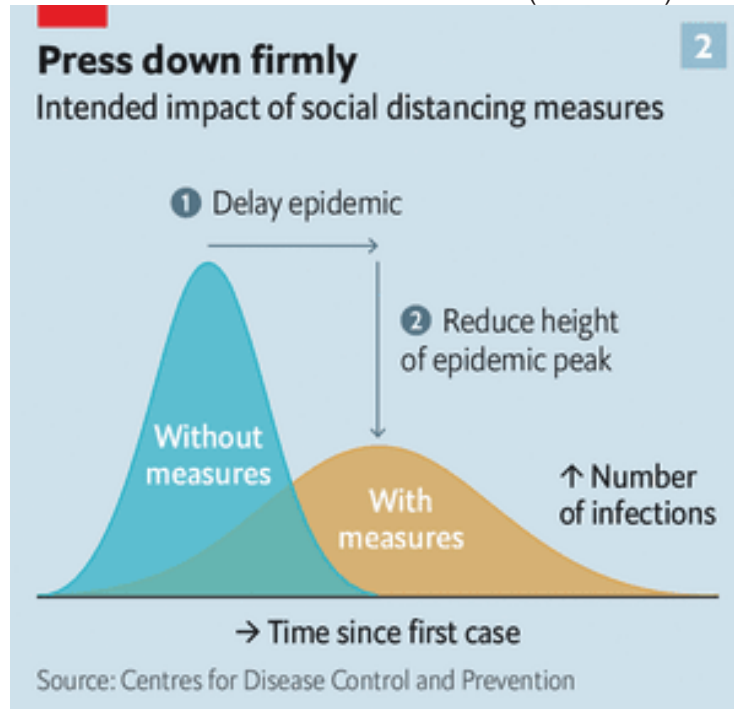
In the case of the COVID-19 pandemic, simplification can be found in the graph “Flatten the Curve” (FIGURE 4). This graph first appeared in an article by the New York Times magazine, and it is a simplification of the original graph made by the CDC and published in The Economist (FIGURE 5). In this case, the simplification came from removing some information and adding the horizontal line titled “healthcare system capacity.”

FIGURE 4 – FLATTEN THE CURVE (SIMPLIFIED).



SOURCE: The New York Times. Available on: <<https://www.nytimes.com/article/flatten-curve-coronavirus.html>>. Accessed: 31 May. 2021.

FIGURE 5 – FLATTEN THE CURVE (ORIGINAL).



SOURCE: The Economist and CDC. Available on: <https://www.economist.com/briefing/2020/02/29/covid-19-is-now-in-50-countries-and-things-will-get-worse>. Accessed: 31 May. 2021.

If, on the one hand, the biggest asset of DV is its synthesis power and the ability to allow people to find patterns and trends (KENNEDY; ENGEBRETSEN, 2020; OTTEN; CHENG; DREWNOWSKI, 2015; RODRÍGUEZ; NUNES; DEVEZAS, 2015), on the other hand, this process is constantly under the influence of designer bias (BRAGA; PONTES E SILVA; SOUTO, 2020).

Another issue that arises from the synthetic nature of DV is the shift towards seeking the 'normal' or 'average,' which can perpetuate the idea of an achievable but unattainable standard (RETTBERG, 2020). By taking large quantities of data and summarizing them, DV reveals less with its overview than the individual assessments (RETTBERG, 2020). For example, when focusing on death trends across a considerable period, interactors can lose sight of the personal meaning of that human life loss (COOLEY, 2020).

3 DATA VISUALIZATION DESIGN

Data visualizations have their own set of rules and internal structure and become harder to read when one is not accustomed to the language they use (TØNNESSEN, 2020).

They generate meaning the same way as any other material, by communicating information using cues that the designer has established and relying on the interactor to follow a pre-determined set of rules to decode what the producer envisioned (LECHNER, 2020). The producer, on their end, will most likely have had these same set of rules when making the visualization, which means the communication is effective because the meaning carried by the visualizations chosen by the producer is already socially defined (LECHNER, 2020).

Different types of graphic representation have different visual language (VON ENGELHARDT, 2002). Therefore, for DV to be successful in communication information, it needs to translate information and, sometimes, create a particular visual language for its intended purpose (VON ENGELHARDT, 2002).

3.1 VISUAL LANGUAGE

Graphic representations are deeply influenced by society and culture and, because of this, in constant change. However, this does not mean that there are no underlying systematic principles essential to consider when making and analyzing DV (VON ENGELHARDT, 2002).

Visual language is defined as “the integration of words, images, and shapes.” (HORN, 1998, p. 11). It is divided into morphology, syntax, semantics, and pragmatics (HORN, 1998), which are further elaborated below:

- Morphology is “the study of the basic individual elements—morphemes and words.” (HORN, 1998, p. 54). Visual language pertains to the essential visual elements, which Von Engelhardt (2002) calls elementary objects.

- Syntax: is how these basic elements can be combined into units. In visual language, it describes how “visual and verbal elements can fit together and in what ways they are combinable” (HORN, 1998, p. 54)
- Semantics: how language conveys meaning and enables communication. How different combinations between verbal and visual elements can convey different meanings.
- Pragmatics: how language is used from a social perspective, what social functions it performs. How people use language in the real world and adapt it to fit different situations. In visual language it involves the application of language to human problem solving, information design, or clear and efficient communication.

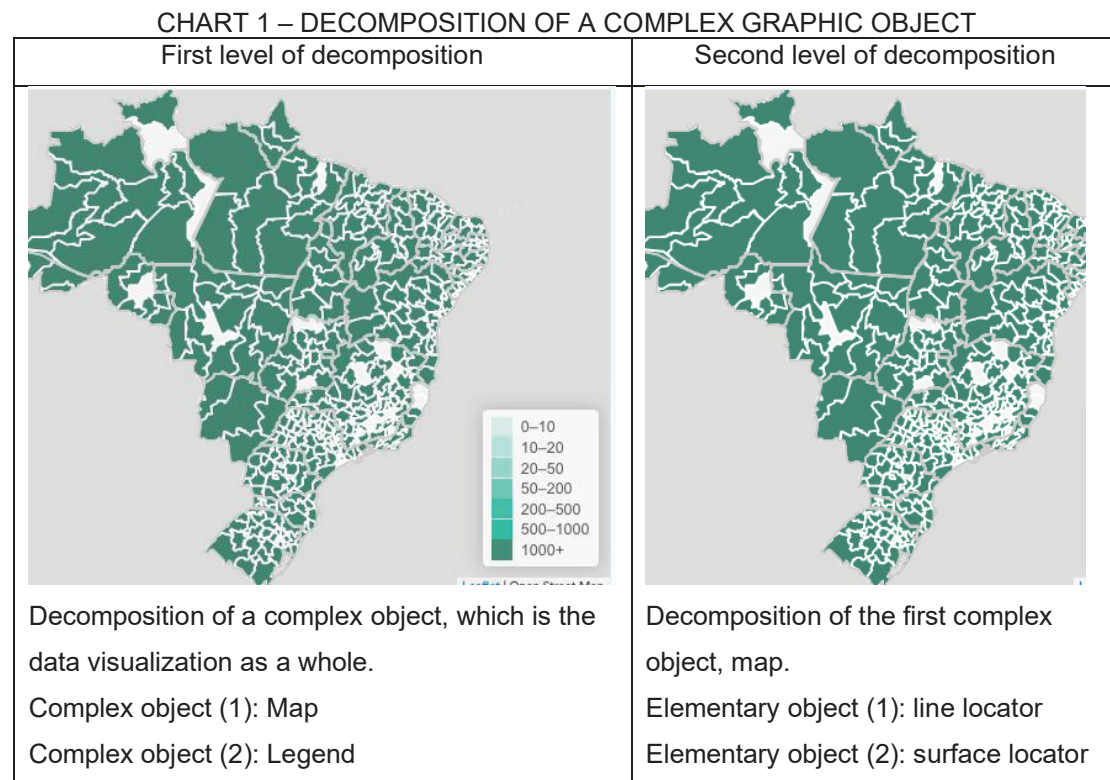
Von Engelhardt (2002) builds on Horn’s proposal for visual language and gathers the theories from Bertin, Tufte, Richards, Tversky, and other researchers to propose a framework for the analysis of graphic representations that can categorize visual elements despite the shifts from society and culture. This framework will be explained next.

Data visualizations are a form of graphic representation and can be divided into elementary and composite (VON ENGELHARDT, 2002). According to the author, elementary graphic objects are the primary elements that cannot be further divided.

Hybrid graphical representations can be described as the nesting of simple representations. It consists of graphic space, visual objects, and graphic relations. Because of this, the interpretation of an elementary graphic object is just that, but the interpretation of a composite graphic object is comprised of: the interpretation of the graphic object, the graphic relations, and the graphic space (VON ENGELHARDT, 2002).

For example, a map with a legend would be a complex graphic representation comprised of the map (complex object) and the legend (elementary object). Von Engelhardt (2002) calls the relationship between these two objects ‘superimposition’ because one element is on top of the other.

However, because the map is also a complex graphic object, there needs to be the second level of decomposition. As you decompose a graphic representation, syntactic roles will appear for each object. These can be, for example: "surface locators," "point locators," or "grid line" (VON ENGELHARDT, 2002). An example of decomposition can be found in CHART 1CHART 7.



SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 23 September. 2021.

When the composite graphic representation is too complex, it is better to decompose it in increments, first separating the representations into categories until one can arrive at the elementary objects.

All elementary graphic objects carry visual attributes, elements of their syntax (VON ENGELHARDT, 2002). Bertin (1988) describes these attributes like color, tonal value, texture, orientation, size, and location in 2D space. Horn (1998) adds to Bertin's attributes and separates the properties of visual syntax into location in 2D space, location in 3D space, valor, texture, color, movement, orientation, size, width, and illumination (HORN, 1998).

Von Engelhardt (2002) builds on Bertin attributes and divides them into spatial and are-fill attributes. For Engelhardt value, grain and color are area-fill attributes, and shape, size, spatial position, and orientation are spatial attributes. Similarly, Börner et al. (2019) mention the same elements, but the authors divide them into graphic symbols (i.e., point, line, icons, etc.) and explicit variables (i.e., form, color, position, etc.)

Aside from attributes, graphic objects can be organized into syntactic structures, which can be object-to-object, or object-to-space (VON ENGELHARDT, 2002). Object-to-space relations are between objects in a specific space. In contrast, object-to-object relations are spatial relations between entities (i.e., clusters, superimposition, lineup, etc.) or attribute-based relations between objects (i.e., objects interacting through variation in size or shape).

Von Engelhard (2002) divided object-to-object relation into spatial clustering, separation by separators, lineup, linking, containment, and superimposition, with objects often in more than one relation. Below follows an explanation of each of the previous:

- Spatial clustering: use of proximity and distance to organize objects into clusters. Results in two or more composite objects made of elementary objects. Groups will often be formed because of separation by separators. Horn (1998) calls this proximal grouping.
- Separation by separators separates graphic objects through space or a graphic partition (i.e., line).
- Lineup: a way to position objects that connects them into a string, with all objects having another object on both sides, except for the beginning and end of the line.
- Linking: This relation involves two syntactic roles: nodes and connectors. A connector is shaped like an arrow, band, or line and anchored to the nodes. Linking can take form as a linear chain, circular chain, tree (branching from one root and with no closed loops), or network (linking that involves one or more closed loops). Horn (1998) calls this a network.

- Containment: This type of involvement needs nodes and containers. A container holds other nodes (graphic objects) by visually surrounding them.
- Superimposition: this involvement needs a foreground object and a background object.

All of the above relations happen within what Von Engelhardt calls meaningful space, where the spatial positioning of objects is subject to interpretation (VON ENGELHARDT, 2002). This means it is a space where objects inside are determined by their relationship to one another. For example, in a graph, the space separating the bars has a meaning. Horn (1998) refers to this as a boundary.

Another facet of meaningful space is distorted metric space, which happens when the represented space is not the same ratio as real-life (VON ENGELHARDT, 2002). For example, subway maps do not accurately portray the distance between stops, as their in-representation distance is not the same as real life.

Within that meaningful space, graphic objects can have different syntactic roles; they can either serve as anchoring for object-to-object, object-to-space, or no anchoring (VON ENGELHARDT, 2002). Object to object anchoring is divided into a node, label, separator, connector, container, and modifier. Space anchored objects can be:

- Point locator: anchored to a specific point in meaningful space (i.e., the location symbol on a Google maps)
- Line locator: anchored to a particular line (i.e., political borders)
- Surface locator: anchored to a specific surface. It locates a surface in 2D or 3D and is fixed in both shape and size (i.e., a lake on a map)
- Volume locator: anchored to a specific volume. Fixed in shape and size (i.e., a 3d area of a 3d chart)
- Metric bar: is "a graphic object in a bar chart that is anchored to two points, extending between them" (p.76). One end of the metric bar is at the baseline, and the other extends to another

point in the graph. It has a fixed length and height but can vary in width and shape.

- Gridline: marks meaningful space (i.e., gridlines in charts). Serves to enable interpretation of object-to-space relations.

Identifying what syntactic role a graphic object has within data visualization is essential to interpret their meaning (VON ENGELHARDT, 2002). For example, when reading a map, one needs to realize the dots showing cities expressly represent a point locator in a metric space and not an unanchored object.

These distinctions matter to interpretation because, for example, it is necessary to interpret two-point locators (cities) as having a relationship with one another depending on their spatial location. If one point is further north than another, the city that point represents is also further north. On the other hand, when the spatial relationship is between a point locator and a label, their relative positions in space do not carry implications (VON ENGELHARDT, 2002).

When two or more elementary objects combine, they create a composite syntactic structure, which is “constructed from two or more basic syntactic structures, through simultaneous combination and/or nesting” (VON ENGELHARDT, 2002, p. 79).

The simultaneous combination is when a set of graphic objects participates in two or more syntactic structures simultaneously (VON ENGELHARDT, 2002). For example, subway markers are linking, separating, and positioning. A graphic object can have more than one syntactic role through simultaneous participation.

On the other hand, nesting happens when a cluster of elements serves as an “elementary” object compared to objects of a higher level (VON ENGELHARDT, 2002). For example, a continent may seem like an elementary object when looking at a global map, but with zoom, the continent appears as nesting of other graphic elements.

Nesting has two sub-categories: background-inset and multi-panel display (VON ENGELHARDT, 2002). The author believes the former is a superimposition of composite graphic objects in another background object

(i.e., legends or labels). At the same time, the latter is a series of composite graphic objects arranged in panels next to each other.

Following the syntactic analysis comes the semantics (VON ENGELHARDT, 2002). Semantics is the interpretation of an elementary graphic object or a composite graphic object. The latter is constructed by analyzing the graphic objects, relations, and graphic space (VON ENGELHARDT, 2002).

Von Engelhardt (2002) divided semantics into four categories: types of correspondence, mode of expression, informational roles, and types of represented information.

Type of correspondence pertains to the relationship between what is represented and the real-world correspondent to the representation (VON ENGELHARDT, 2002). It is further divided into:

- Literal: similar to the physical object or structure it's meant to represent.
- Metaphoric: based on an analogy between the representation and the meaning.
- Arbitrary-conventional: a convention makes the representation signify the meaning (i.e., the biohazard symbol).
- Rebus-based: when the spoken word for the representation sounds like the word for the meaning.
- Metonymic: the representation has some form of physical involvement with the meaning (i.e., is a part of, plays a role in, is a possible result of, etc.)

Following the type of correspondence comes the modes of expression graphic objects can have. They are divided into pictorial or non-pictorial. Pictorial corresponds to its real-world referent. Non-pictorial elements, on the other hand, are the ones that have no literal correspondence to either its intended or intermediary referent (VON ENGELHARDT, 2002).

Additionally, graphic objects might have different informational roles: informational objects, reference objects, and decoration objects (VON ENGELHARDT, 2002). Within information design, decoration objects should

be used with caution as they tend to confuse and distract the interactor (MAYER, 2003). These elements are further explained below:

- Information objects: the elements that have to be adjusted if the data corresponds to the changes (i.e., the bars in bar charts or the colors in a weather map).
- Reference objects: serve to interpret the information objects but would not have to be adjusted if the data changed. They can be sub-divided into spatial reference objects and legend objects:
 - Spatial objects: mark meaningful space.
 - Legend objects: explain symbols and visual attributes.
- Decoration objects: could be erased without affecting the interpretation of the data or the data itself.

Visual features (such as color, texture, or shape) might also be classified by their informational role as informative or decorative (VON ENGELHARDT, 2002).

Additionally, other elements that can be added to the study of semantics are the interactions that DV can garner from interactors (i.e., zoom, search, filter function, etc.) (BÖRNER; BUECKLE; GINDA, 2019).

Lastly, the framework discusses the possible classification of graphic representation. Von Engelhardt divides the distinctions of visual representation into nine primaries and six hybrid types. The hybrid types are a combination of two or more of the primary types. The primaries are picture, statistical chart, time chart, link diagram, grouping diagram, table, composite symbol, and written text. The hybrids either mix two primaries, a primary and a hybrid, or two hybrids. They are statistical map, path map, statistical path map, statistical time chart, statistical link diagram, and chronological link diagram. Börner et al. (2019) add to this classification: graphs, trees, and networks. CHART 2 shows these different types of classification, as well as its possible combinations.

CHART 2 – POSSIBLE CLASSIFICATIONS OF GRAPHIC REPRESENTATION

	Statistical chart	Link diagram	Statistical link diagram
Map	Statistical map	Path map	n/a
Time chart	Statistical time chart	Chronological link diagram	n/a

Link diagram	Statistical link diagram	n/a	n/a
Path map	n/a	n/a	Statistical path map

SOURCE: Von Engelhardt (2002)

Additionally, the authors classify DV by: the insight needs of the user, data scale, and type of analysis done to the data. The insight needs of the interactor are what the interactor needs to absorb from the visualization and why they are viewing it in the first place. They can be divided into: categories/clusters, order/rank/sort, distribution, comparisons, trends, geospatial, compositions, correlations/relationships.

Data scale and analysis are about how the data was treated before it was transformed into visualization. Data scale can be: nominal, ordinal, interval, or ratio; while the type of analysis is divided into: statistical, temporal, geospatial, topical, and relational (BÖRNER; BUECKLE; GINDA, 2019).

3.2 DATA VISUALIZATION AS EMOTION

Data visualizations use form, color, and composition to make people perceive them as aesthetic and bodily experiences (KENNEDY; ENGBRETSSEN, 2020). Visual elements create meaning and generate feelings, which are people's emotional responses during an interaction. Both are inseparable when interacting with a piece of media (KENNEDY; ENGBRETSSEN, 2020).

Emotional involvement is tied to aesthetics (KENNEDY; ENGBRETSSEN, 2020). Kennedy and Engbretsen (2020) established three ways to involve with DV emotionally: the actual interaction with the DV (when one engages *with* it), the emotional and practical responses (when one is engaged *by* it) and, audience response (when one becomes engaged *because* of it).

Another integral part of how people become emotionally involved in what Brinch (2020) calls 'beauty.' When the reader perceives a DV as beautiful, they become interested enough to invest their time and effort into understanding the phenomenon (BRINCH, 2020). According to the author, there are five types of beauty:

- Fine craftsmanship: when the beauty comes from being able to see the skills the designer had to have to present information in that particular way;
- Complexity into comprehension: this beauty comes from transforming complex or intricate data into comprehensible and accessible DV. This type of beauty, however, risks oversimplification and, with it, loss of meaning (HEPWORTH, 2016; RETTBERG, 2020);
- Fixed complexity: beauty that comes from preserving the complexity of a dataset. The creators choose to maintain all the complexity of the data and use it to situate the user.
- Beauty from action: beauty helps people engage emotionally or cognitively with DV, study them, and take action.
- Beauty as art: DV is art projects as much as informational media pieces. A DV is made to serve a purpose, and if it is later judged to be good enough, it will be considered art. This research was elected not to analyze this type of beauty as it fell beyond the project's scope.

Beauty is an element in what Gray (2020) names the 'sublime,' or the factors that produce strong emotions. This does not seem to fit with the idea of simple language and neutrality that DV carries. However, as mentioned before, DV brings stories and has meanings, despite their simplified visual aspects.

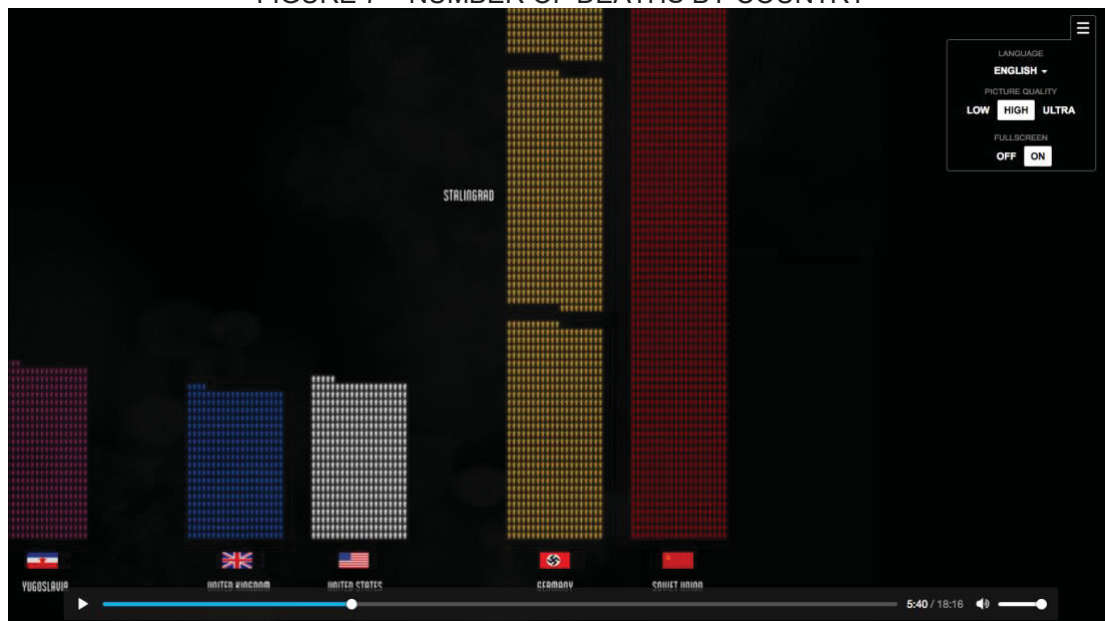
The use of simplification does not necessarily mean emotionless representation. Gray (2020) explores this idea in the interactive documentary 'The Fallen World War II' (figures 6–8) where DV was used to showcase the weight of death during the war.

FIGURE 6 – NUMBER OF CIVILIANS REPRESENTED BY ICON



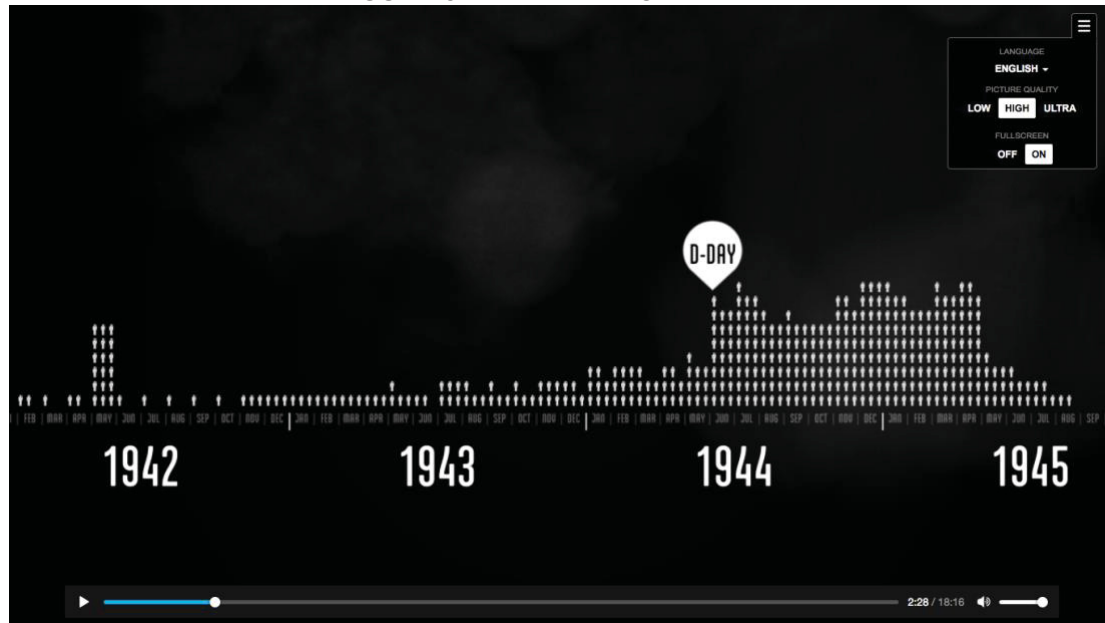
SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 7 – NUMBER OF DEATHS BY COUNTRY



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 8 – TIMELINES OF DEATHS



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

The short animation uses many graphic elements correlated with data visualizations (i.e., bar graphs, icons, and timelines). Still, through the use of narration and perspective-shifting, it also highlights an impactful story about the nature of human loss during a war (see figures 9–16).

This data visualization shifts in perspective, switching between a photograph showcasing the individual human loss and a large graph showing the war's casualties. This alternation infers the narrative of life and death and gives it the weight of death (GRAY, 2020). For example, there is an instance where a soldier is about to shoot a mother and child. This representation becomes an outline, which then joins multiple others like it and showcases the scale of death. Figures 9–16 show the changes in abstraction.

FIGURE 9 – MICRO TO MACRO (PART 1)



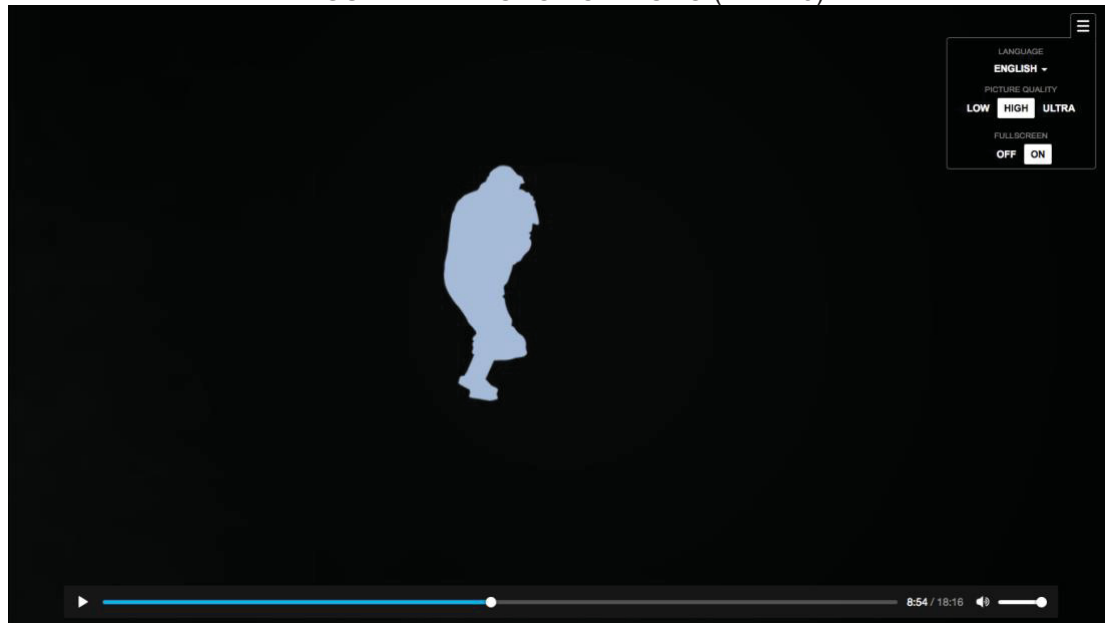
SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 10 – MICRO TO MACRO (PART 2)



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 11 – MICRO TO MACRO (PART 3)



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 12 – MICRO TO MACRO (PART 4)



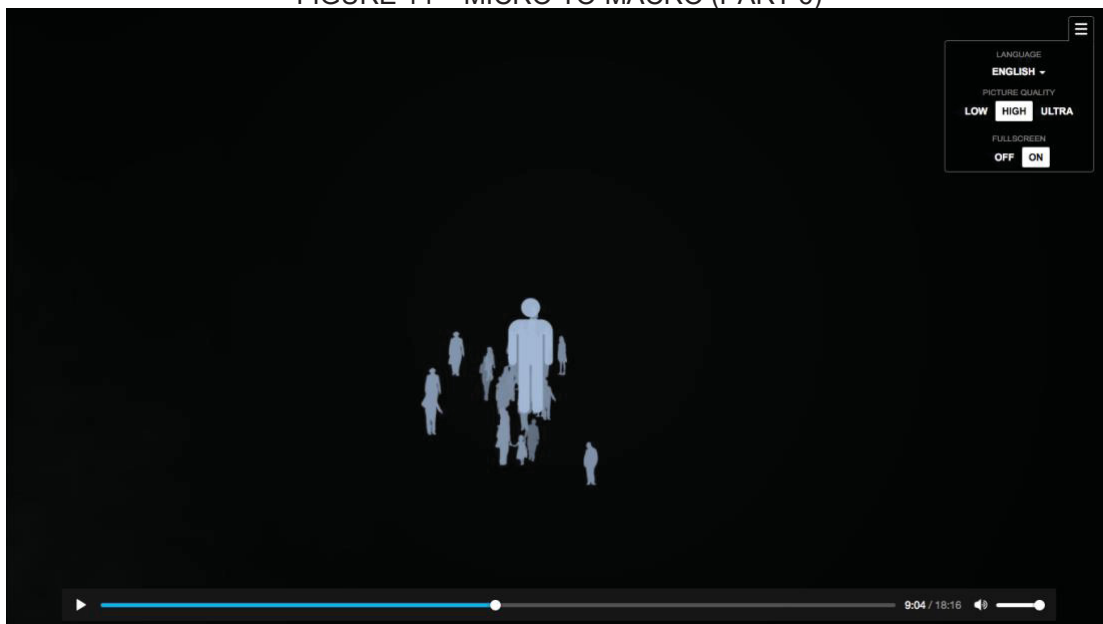
SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 13 – MICRO TO MACRO (PART 5)



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 14 – MICRO TO MACRO (PART 6)



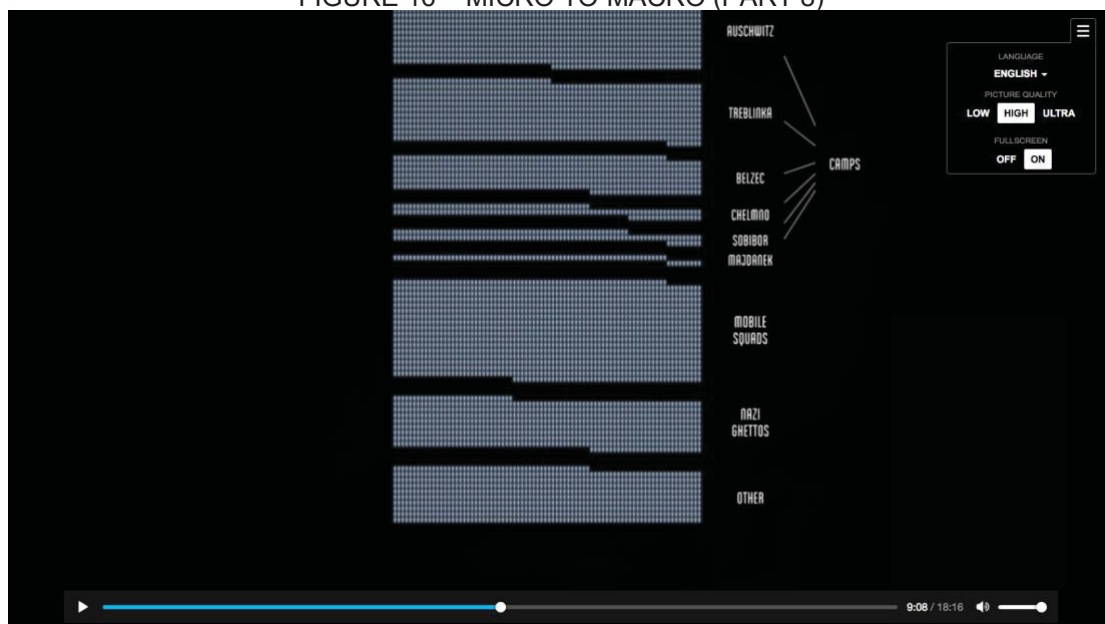
SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 15 – MICRO TO MACRO (PART 7)



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

FIGURE 16 – MICRO TO MACRO (PART 8)



SOURCE: The Fallen of WWII. Available on: <<http://www.fallen.io/ww2/>>. Accessed: 25 May. 2021.

3.3 ELEMENTS FOR THE ANALYSIS OF DATA VISUALIZATION

Using the theories discussed in chapter 3, an annotation chart was compiled (CHART 3), comprising of the framework proposed by Van

Engelhardt (2002) and the views of Gray (2020), Brinch (2020), Weber (2020), Börner et al. (2019), and Ryan (2007).

CHART 3 – ELEMENTS OF DV, SYNTHESIS

SYNTACTIC		
Composite syntactic structures		
Simultaneous combination Nesting	Background inset	
	Multi-panel display	Graphic multiple Shared-axis multi-panel
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation
	Area fill attributes	Value Grain Color
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition
	Object-to-space	Metric space Distorted metric space
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Grid lines
	No anchoring	
SEMANTIC		
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional	
Mode of expression	Pictorial Non-pictorial	
Informational roles	Information objects	

	Reference objects	Spatial objects
		Legend objects
	Decoration objects	
Interactions	Zoom Search and locate Filter Details on demand History Extract Link and brush Projection Distortion	
CLASSIFICATION OF GRAPHIC REPRESENTATIONS		
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network	
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram	
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	
Data scales	Nominal Ordinal Interval Ratio	
Analysis	Statistical Temporal Geospatial Topical Relational	
ELEMENTS OF ENGAGMENT		
Storytelling	Narrator	

	Tellability
	Sequentially
	Temporal dimension
Perspective shifting	

SOURCE: the author based on Brinch (2020), Gray (2020), Weber (2020), Börner et al. (2019), Ryan (2007), and Von Engelhardt (2002).

The interactor can become involved with a DV (HEPWORTH, 2016). However, to make an informed choice, or take action, the DV needs to incite in the interactor a feeling of agency so they can take control of their own lives (MASSON; ES, 2020). The following section discusses agency and how media can foster it.

4 AGENCY

According to Murray (1997, p. 126), agency is “the satisfying power to take meaningful action and see the results of our decisions and choices.” Agency is not equal for everyone as their experiences influence how agency is perceived (EICHNER, 2014).

Activity alone is not agency. One can have a limited set of possible actions (such as chess) and still experience agency because those limited choices have consequences and change the game. The more a choice impacts a person's environment, the more they will experience agency, even if the choice/action is harmful to the person taking it (MURRAY, 1997). However, when things go right, one can feel like giving instructions and acting simultaneously. This is the feeling of agency (MURRAY, 1997).

While Murray focuses on agency as an act, Eichner (2014) says that taking action is less important than the perception of possible action taking. For the author, the possibility, or *perceived agency*, can be just as powerful as the acting in itself. Tanenbaum and Tanenbaum (2009) add to Murray's concept and define agency as a commitment to meaning, emphasizing a narrative choice and immersion rather than a perceived sense of unlimited freedom. For the authors, agency does not come from simply acting within a world but expressing intent and receiving feedback. What is most important is not to have an action performed but merely to have the possibility to work if chosen (EICHNER, 2014).

Any piece of media can foster agency in the user. Fostering can be done interactively, in a game, or with perceived interaction, such as in a movie (BIZZOCCHI, 2005). In non-interactive media, such as movies or data visualizations, agency can be fostered through narrative structure, which is a part of what Eichner (2014) calls personal agency. The author situates agency into three levels: personal agency, creative agency, and collective agency, further explained below.

Personal agency is the most common and basic of agencies, and the other two types can only exist after one perceives personal agency (EICHNER, 2014). It can be perceived through four kinds of mastery: narrative, choice, action, and space (EICHNER, 2014).

To master narrative, one needs to identify the media genre they interact with and can predict how the story will unfold. When the narrative follows what was expected, a sense of pleasure comes from seeing where the story was going all along (EICHNER, 2014). An example of this is Superhero movies, where the end is evident to the point of being formulaic, but it is precisely that predictable format that entices the fans.

However, when media subverts the user's expectations, interactors can get lost in the narrative and thus resort to communities to understand the subversion, creating collective agency (EICHNER, 2014). Mastering choice happens when the interactor realizes they can make a choice. When a choice is made, agency is evolved, no matter if the consequences are favorable or not. However, if there is too much freedom of choice (like in open-world video games), a meaningful commitment is likely to support agency (TANENBAUM; TANENBAUM, 2009).

Mastering action is when the interactor acts with their body and watches as it happens via the controller or mouse in the digital world. Bizzocchi (2003) describes this when he analyses the game *A Ceremony of Innocence*, where the movement of the mouse acts as an extension of the human body, and it makes the interactor perceive agency when the mouse moves in the same way as the human body would. This type of agency is not restricted to interactive media. One can perceive agency through action in 'unilateral' media. Eichner (2014) explains this by describing the sense of agency when watching reality TV and deciding to pick up the phone to vote.

Lastly, mastering space is what Murray (1997) identifies as the act of moving through space. For this to happen, a person needs to control the movement properly. For example, there is frustration instead of agency if one does not understand how video game control works and cannot manage the character effectively (e.g., bumping into things). When space becomes vital in a narrative, spatially navigating becomes one of the activities the interactor engages in, and it triggers mastering of space, which can incite agency (MURRAY, 1997).

Once one perceives personal agency, they can move onto creative agency, engaging with media beyond the actual interaction (EICHNER, 2014). A typical example is hackers and mod makers being a part of the gaming

community and mods being considered an active part of gameplay despite being 'outside of the game.' Eichner (2014) calls creative agency this freedom and possibility to create.

Parallel to creative agency, Eichner (2014, p. 174) describes collective agency as “fan engagement on a meta-text level.” This type of agency evolves through interactions between fans, creators, and producers, where each interaction makes the feeling of agency increase and circulate. This agency is the only one that does not hinge entirely on the object but the community. CHART 4 summarizes the levels of agency and the elements that foster them, that will be used to analyze the sample.

CHART 4 – ELEMENTS OF AGENCY, SYNTHESIS

Levels of Agency		
Personal Agency	Mastering action	When the interactor acts with their body and sees the digital world change in accordance to the action they took in the real world
	Mastering narrative	When one identifies the genre of media, they are interacting with and can predict how the narrative will unfold
	Mastering choice	When the interactor realizes they can make a choice
	Mastering space	When the interactor can move through space through an understanding of how the mechanics of movement work for that piece of media
Creative Agency		The possibility to engage with media beyond the interaction, through creativity and intervention
Collective Agency		Fan engagement through interactions between fans, creators, and producers

SOURCE: the author based on Eichner (2014) and Murray (1997)

Because people rely on DV for making decisions, designers should look to make DV that fosters agency (MASSON; ES, 2020). When the interactors are versed in the language of DV and can process the elements that support agency, they can become agents in their own lives (TØNNESSEN, 2020) and hopefully make better choices for themselves and those around them. However, the DV used during the COVID-19 pandemic deals with sensitive data, specifically, data about death. The following section explores how interactors perceive and process information relating to death to understand better how DV's design can impact agency and personal choices.

5 DEATH AWARENESS

As stated in the introduction, dealing with death is a complicated process. The idea that life is not forever and the unknown of what comes next occupies much of society's concern (BECKER, 1973). Media constantly explores death, after-life, immortality, and more, in both positive (e.g., *The Good Place*, *Over the Moon*, etc.) and negative lights (e.g., *Bojack Horseman*, *The Old Guard*, etc.).

Psychology is filled with theories on how society reacts when faced with the inevitability of death. For this research, two were chosen: the Terror Management Theory (TMT) and the Terror Management Health Model (TMHM).

Terror Management Theory explores existential terror and anxiety and how people evolved to control this terror. This theory is the basis for the second theory to be used, the Terror Management Health Model (TMHM), which explores how people make choices regarding their health and well-being when confronted with the prospect of dying.

These two theories were selected because they tackle how people make choices and behave. The TMHM was considered especially relevant as it deals specifically with death awareness and its consequences for health-related decisions, which is relevant in the context of a pandemic.

5.1 TERROR MANAGMENT THEORY

Terror Management Theory (TMT) poses that humans are biologically wired for survival and self-preservation, but have developed enough cognitive abilities to grapple with the inevitability of death constantly, a dissonance that causes anxiety and an ever-present sense of existential terror (GOLDENBERG; ARNDT, 2008; GREENBERG; ARNDT, 2012)

This terror is managed by an anxiety buffering system comprised of cultural worldviews, self-esteem, and close interpersonal relationships (PYSZCZYNSKI *et al.*, 2020). Cultural worldviews provide people with beliefs that deny the precarious nature of existence and promise literal or symbolic immortality (GREENBERG; ARNDT, 2012; PYSZCZYNSKI *et al.*, 2020).

Literal immortality comes, for example, from religions that believe in life after death or reincarnation. They give people the sense that death is not the end for their souls. On the other hand, symbolic immortality comes from believing in ideologies that make oneself part of something bigger, such as a cause. They pose that by standing by a set of beliefs, they will be a part of something greater that will live on after their deaths (GOLDENBERG; ARNDT, 2008; GREENBERG; ARNDT, 2012; ROSENBLATT *et al.*, 1989).

Self-esteem is described as a "sense of personal value that results from believing that one is living up to the standards of one's cultural worldview" (PYSZCZYNSKI *et al.*, 2020, p. 2). And finally, close relationships provide external validation for one's worldviews and boost self-esteem, strengthening belief in that worldview. This triadic system manages existential terror by delivering comfort in living a meaningful life (PYSZCZYNSKI *et al.*, 2020).

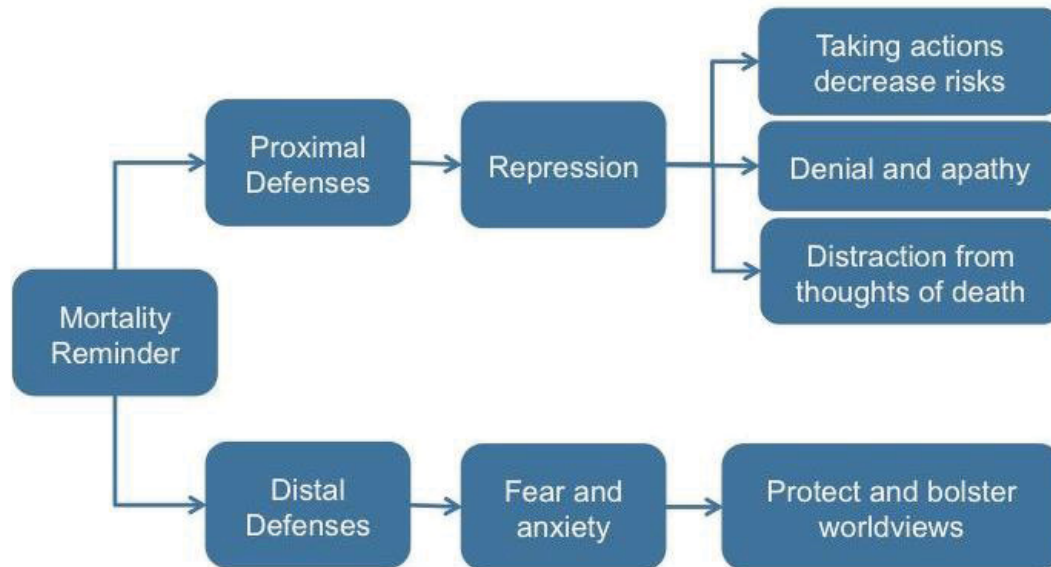
For TMT to happen, one needs to be exposed to morality reminders. These reminders can trigger distal or proximal defense mechanisms (HARMON-JONES *et al.*, 1997). According to this model, proximal defenses are activated when actively pushing the death reminders away from consciousness by distancing oneself from the reminder of death in the environment.

On the other hand, distal defenses are sub-conscious and always active, operating whenever the individual is awake. They operate implicitly and provide the individual with a significant reality that defends them against sub-conscious thoughts of mortality (PYSZCZYNSKI; GREENBERG; SOLOMON, 1999). Figure 17 (page 59) shows a simplified version of the Terror Management Theory.

Research on mortality often accompanies two complementary theories: "mortality salience" and "anxiety buffer" (FRIEDMAN; RHOLES, 2007). Mortality salience states that if individuals have a set of beliefs that protect against death-related concerns, then a person's belief in that set of principles will increase when they are reminded of death. This means that after being confronted with death, people will more strongly cling to their ideals.

The anxiety buffer hypothesis states that a person has a psychological structure that buffers death-related concerns. If that structure is weakened, the person's awareness of their mortality will increase (FRIEDMAN; RHOLES, 2007).

FIGURE 17 – TERROR MANAGEMENT THEORY DIAGRAM



SOURCE: the author, based on Greenberg and Arndt (2012)

However, for the anxiety-buffering system to work, two things need to happen: (1) one must believe in that their worldview is correct, and (2) one must believe that they are holding up or exceeding the values held by the worldview (ROSENBLATT *et al.*, 1989).

This becomes complicated when considering that cultural values are constantly threatened, as they are socially constructed fictions and vulnerable to different options or social validation. It can become difficult to hold those worldviews when differing opinions appear. People tend to either confront that their beliefs are not universally valid or consider the transgressor evil (GRANT; WADE-BENZONI, 2009; ROSENBLATT *et al.*, 1989). Of the two, it is much easier to view the transgressor as evil than to admit to their non-universal worldview.

Stein and Cropanzano (2011) have argued that TMT tends to increase belief in your worldview and foster mistrust of those that exist outside of it—for example, punishing behavior one considers immoral after a tragedy or hiring people that are similar to oneself after death-related stress.

For the case of the COVID-19 pandemic, the fragility of this system becomes more pronounced, as discussed by (PYSZCZYNSKI *et al.*, 2020), who argued that because of the current state of the world, managing TMT is far more complex as a health measure designed to keep people safe sometimes go against those support systems (e.g., social distancing actively interferes with close relationships).

Letting existential terror go unmanaged can have detrimental consequences for mental states and habits. When first confronted with thoughts of death, an individual might engage in behaviors to protect the physical self. However, the delayed effect of mortality salience may instigate acceptable self-esteem behaviors, which lead to more risky behavior (GREENBERG; ARNDT, 2012).

When engaging in proximal defenses (e.g., when thoughts of death are in focus), people tend to push them aside by either engaging in behaviors that focus on avoidance (e.g., deny perceived risk) or decrease the likelihood of a potential threat (e.g., taking steps to lower death threats) (GOLDENBERG; ARNDT, 2008). Conscious thoughts of death lead to health over beauty, but unconscious lead to beauty over health decisions (GREENBERG; ARNDT, 2012).

However, when thoughts of death are sub-conscious (e.g., distal defenses), the tendency is to experience fear and anxiety, and resort to self-esteem and worldviews to manage that terror. The mere thought that there are different worldviews can threaten one's beliefs and make people more violent towards those that are different and more lenient towards those that uphold the same values (GOLDENBERG; ARNDT, 2008; HEPWORTH, 2016; ROSENBLATT *et al.*, 1989; STEIN; CROPANZANO, 2011). In such a stressful situation, people tend to cling towards simple worldviews that paint them as the heroes in the story (imaginary immortality) and support the thought of "we are good, they are evil," evil being everyone different and challenged their worldview.

"When confronted with explicit thoughts of death, people react by trying to avoid the threat or by trying to reduce its likelihood with health-promoting behaviors" (GREENBERG; ARNDT, 2012, p. 407).

The key to a healthier coping mechanism is identifying worldviews

that provide accessible venues and minimizing the cost to those inside and outside the culture (GREENBERG; ARNDT, 2012). It is imperative to foster solid bases of self-worth and safe attachments to lessen the destructive tendencies that often come with reminders of death. When people have secure bonds and attachments, they respond with kindness instead of violence (GREENBERG; ARNDT, 2012).

The way one receives a mortality reminder also impacts their behavior. When people are presented with mortality reminders for a more extended period or in a way that is consistent with their internal goal structure, they become more intrinsically motivated and adopt healthier behaviors (LYKINS *et al.*, 2007).

Encouraging intrinsically oriented people to engage in death reflection might lead to post-traumatic growth and increase intrinsic goals. As for extrinsically motivated people should be encouraged to engage in after-death reflection and their current life goals. Those might help promote post-traumatic growth and, over time, influence them to shift towards more intrinsic goals (LYKINS *et al.*, 2007).

5.2 TERROR MANAGMENT HEALTH MODEL

The Terror Management Health Model (TMHM) was created by (GOLDENBERG; ARNDT, 2008) and discusses the unique implications of death awareness and existential terror to health-related behaviors.

TMHM integrates TMT and health psychology, providing a foundation for understanding the external influences for motivational landscapes and everyday health decisions (GOLDENBERG; ARNDT, 2008).

It states that people are motivated to take beneficial health measures when thoughts of death are conscious. However, when those thoughts are activated subconsciously, the health motivation becomes more self-relevant (e.g., clinging to worldviews and beliefs that are not necessarily beneficial to health and well-being) (GREENBERG; ARNDT, 2012). The theory states that:

1. People are motivated to reduce health-relevant concerns when they directly assist in activating death awareness. This can happen in two different ways, either as healthy behaviors that

make death seem less imminent (e.g., adopting healthier lifestyles) or avoiding the perceived threat as a means to distance yourself from the possibility of dying (e.g., denial of perceived threat).

2. Unconscious thoughts of death override health motivations. This does not mean that the outcome will be necessarily unhealthy, but the primary reason behind it is not keeping oneself healthy but denying the threat of death.
3. In the context of non-conscious death awareness, health outcomes are related to the involvement with a physical body. The more people are reminded of their physicality, the less they can effectively defend themselves against non-conscious mortality reminders.

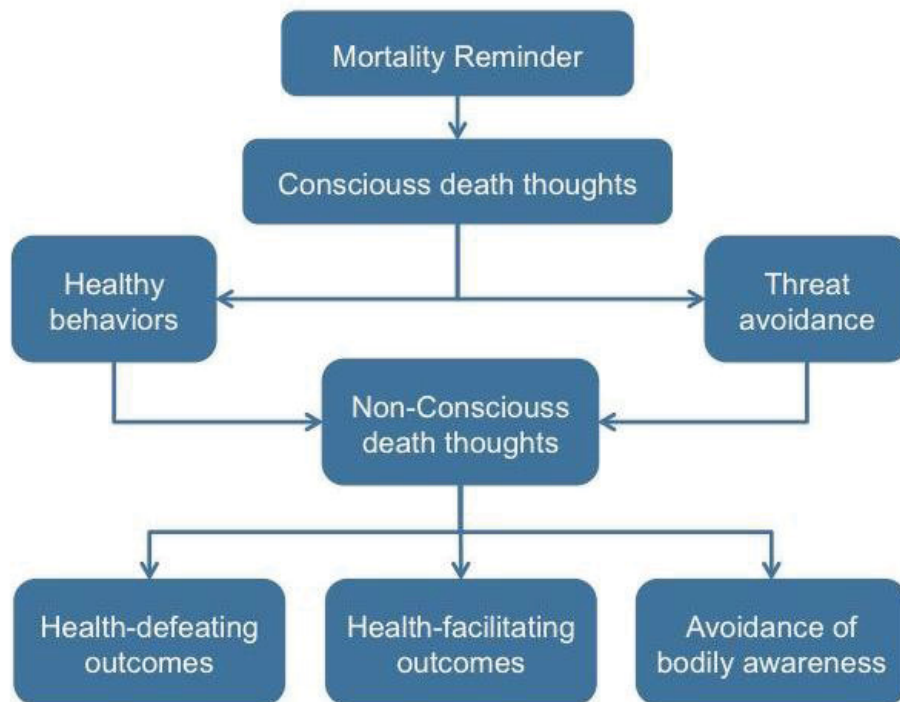
Goldenberg and Arndt show that, across literature, conscious death awareness causes people to seek ways to remove these thoughts from focus. People can do that by making themselves stronger and healthier (healthy behavior), ignoring the threat, and lowering perceived danger (threat avoidance).

When thoughts of death aren't in the conscious mind, people are more likely to engage in behavior that boosts their self-esteem, even when they go directly against health guidelines (figure 18, page 63) (GOLDENBERG; ARNDT, 2008). TMHM explains why long-term compliance with health guidelines is challenging, especially once the immediate threat leaves the focus of attention.

However, better ways to promote healthy behavior include adaptive coping strategies, health optimism, response efficacy, and perceiving oneself as less vulnerable (GOLDENBERG; ARNDT, 2008). Those can push people to react more constructively to conscious psychological death threats.

The authors argue that understanding the effects of mortality awareness through TMT may enable health promotion by exploiting death awareness triggers' responses. It is especially relevant to consider how one can affect self-esteem and worldviews when promoting healthy behavior as a strategy to foster prosocial behavior (GOLDENBERG; ARNDT, 2008; GRANT; WADE-BENZONI, 2009; GREENBERG; ARNDT, 2012).

FIGURE 18 – TERROR MANAGEMENT HEALTH MODEL DIAGRAM



SOURCE: the author, based on Goldenberg and Arndt (2008)

5.3 DEATH ANXIETY VS. DEATH REFLECTION

One crucial element to TMT and TMHM is mortality reminders (MR), which allow people to engage in either death anxiety or death reflection (GRANT; WADE-BENZONI, 2009).

These two types of death thoughts differ in people's cognitive processes and consequent behaviors. Grant and Wade-benzoni (2009) separate them into processed by a "hot" system (death anxiety) and a "cold" system (death reflection).

Death anxiety is the emotional state of death awareness that incites fear, panic, and dread about one's mortality (GRANT; WADE-BENZONI, 2009). It is a state processed by the "hot" cognitive system, causing immediate, emotional, visceral, impulsive reactions (METCALFE; MISCHEL, 1999).

Terror Management Theory is active in these "hot" systems and causes the self-preservation instincts to activate. Therefore, TMT can be categorized as effect-driven or reactive, meaning people will have visceral emotional responses to the remainder of their mortality, leading to more self-

absorbed acts of preservation (GOLDENBERG; ARNDT, 2008; GRANT; WADE-BENZONI, 2009).

On the other hand, death reflection is a cognitive state of death awareness, which re-contextualizes one's lives and fosters contemplation of meaning, purpose, and thoughts about how one will be remembered after death (GRANT; WADE-BENZONI, 2009). It is processed in the "cool" cognitive system, which deliberates, analyses, and reacts rationally based on one's intentional control (METCALFE; MISCHEL, 1999).

Grant and Wade-benzoni (2009) highlight three differences between death reflection (DR) and death anxiety (DA): emotionality, duration, and focus of attention.

Death anxiety garners extreme and vivid guttural emotions, while DR causes controlled thoughts. As it engages the "hot" system, DA focuses on specific events and triggers that last for a short period. On the other hand, DR can span many months or even years because of its intentional extended contemplative nature.

As for focus, DA emphasizes protecting the self, while DR promotes positive changes for others (GRANT; WADE-BENZONI, 2009).

While death anxiety often leads to TMT, death reflection can become a trigger for Post-Traumatic Growth (PTG), which happens after a struggle with challenging life events (LYKINS *et al.*, 2007). After the trauma, people shift to intrinsic motivation and are more likely to seek to build meaningful and lasting resources that satisfy human needs (e.g., closer relationships, better the world), leaving external motivations behind, such as building shallow resources and meeting superficial needs (e.g., make money, obtain beauty).

Mortality reminders affect whether someone will engage in PTG, focus on prosocial behaviors, or activate TMT's self-defense systems. For TMT, the mortality reminder is often causal, short-term, and is processed quickly and instinctively by a "hot" cognitive system (GRANT; WADE-BENZONI, 2009; LYKINS *et al.*, 2007).

Post-Traumatic Growth, on the other hand, has mortality reminders that coexist with other changes in one's life, is long term and reflective, promoting death reflection and resulting in increased intrinsic motivation

(GRANT; WADE-BENZONI, 2009; LYKINS *et al.*, 2007). CHART 5 summarizes the elements of death awareness used to analyze the sample.

CHART 5 – ELEMENTS OF DEATH AWARENESS, SYNTHESIS

Mortality reminder types		
Hot System	Visceral	Instills feelings of disgust, horror, fear, etc.
	Self-protective	It appeals to the fear of mortality, which makes the buffer system seek internal validation
	Fear inducing	Focuses on the negative, the tragedy and horror of death
	Fast and short	Short but intense duration of mortality reminder
Cool System	Analytical	Instills feelings of reflection, stripping the horror from death
	Prosocial change	Appeals the interactor to reflect upon death and encourages social changes to make a better place before dying
	Reflection inducing	Focuses on positivity and presents the inevitability of death as a fact and not an unknown horror
	Long-term	The MR is long term (often many years) and not too intense

SOURCE: the author, based on Grant and Wade-Benzoni (2009), Goldenberg and Arndt (2008), Lykins et al. (2007) and Metcalfe and Mischel (1999)

6 FINAL OBSERVATIONS FROM THE LITERATURE REVIEW

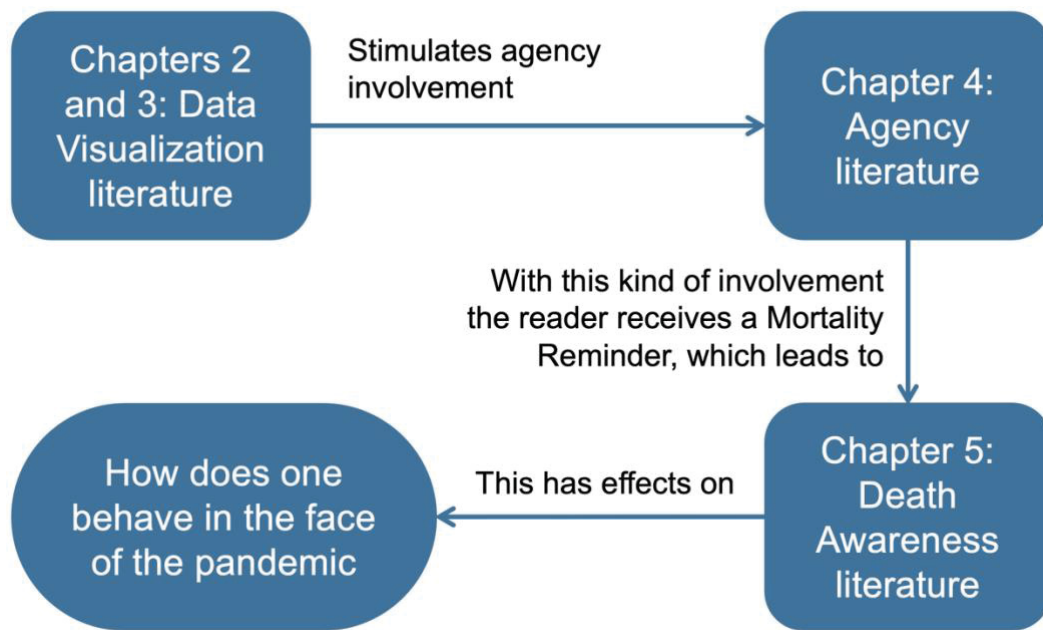
The topics reviewed in these last three chapters act as a progression diagram describing how one interacts with a DV and its implications for personal choices and behaviors.

Chapters 2 and 3 talk about the elements identified in the data visualization literature. Those elements stimulate the interactors to engage with the DV and begin some kind of involvement with the media, in this case, through agency. Eichner (2007, p.127) defines involvement “as the general attachment to any media text with both cognitive and emotional activities of the recipient.”

From there, chapter 4 covers agency and how an artifact can foster it. With this kind of involvement, the interactor might perceive the mortality reminders littered across the COVID-19 data visualizations and begin the psychological process of becoming aware of death (chapter 5). From this awareness come the theories of TMT and TMHM, which provide insights into how DV can impact and dictate personal behavior and choices.

This group of theories answers the first specific question of this dissertation. FIGURE 19 summarizes the literature review’s main contributions.

FIGURE 19 – LITERATURE REVIEW DIAGRAM



SOURCE: the author

7 METHODOLOGY

7.1 TYPE OF RESEARCH

This study is based on qualitative research, and it was chosen because of the lack of available information about the phenomenon studied (GREEN; THOROGOOD, 2004). The method was divided into 3 phases: (1) problem comprehension, (2) object and context analysis, and (3) analysis and results.

The initial phases were exploratory and the latter explicative (SANTOS, 2018). The exploratory part was meant to comprehend the particular combinations of the phenomenon to be studied. The explicative part was used to analyze previous theories and verify the results.

This method was chosen for its qualitative and interpretive approach as it assesses the meanings and relationships between different components of the same system. It follows the inductive logic in which an individual phenomenon is analyzed for later generalization. This logic focuses on observing effects or results from a specific phenomenon, looking to answer the questions of “how?” and “why?” (SANTOS, 2018).

The first phase focused on a systematic literature review (SLR) and narrative literature review (NLR). The systematic review was conducted using the keywords “data visualization,” “covid-19”, and “death awareness.” This phase sought to understand the research question and refine the main objective. It also served the exploratory role of gathering examples of data visualization and compiling the most prominent modes of representation into a sample. This phase mapped out how DV has been used to represent death in the context of COVID-19 and served to build the analysis tool that was used in phase 2.

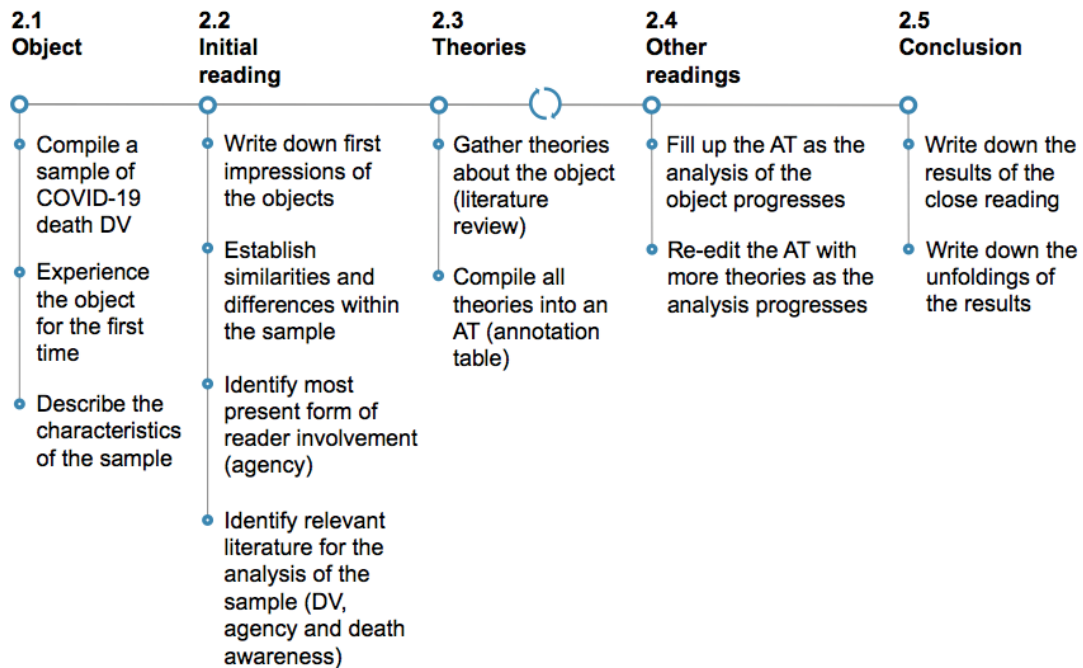
The second phase analyzed how COVID-19 visualizations supported death awareness and agency using Close Reading. Close Reading is a qualitative and subjective method that generates valuable insight if performed systematically (BIZZOCCHI, 2005). It is the process of meticulously analyzing a piece of media until one can effectively describe all its meanings and flaws (BIZZOCCHI; BEN LIN; TANENBAUM, 2011).

The method of Close Reading has been applied to analyze objects under specific lenses (BIZZOCCHI; BEN LIN; TANENBAUM, 2011). Methods similar to close reading have been used for data visualizations and consider how one interacts with the information in a DV and how that DV fosters emotional involvement (SIMPSON, 2020). These have provided important insights into how DVs are constructed to derive specific emotive responses from the interactors. In the case of this study, the analytical lens is the feeling of agency and mortality awareness.

This phase comprised five steps, based on the combination of the class notes from the supervisor, Professor Fadel (FADEL, 2020), and the method of analysis proposed by Von Engelhardt (2002), summarized in figure 20. The steps are:

1. Object: the goal is to gather a sample of DV, experience them for the first time, and describe their main characteristics and points of contact.
2. First reading: The most relevant design elements and the most striking visual elements are highlighted.
3. Theories: relevant approaches to the sample analysis are collected and compiled into an annotation chart (AC). The results from this phase are further explained in section 3.2.
4. Other readings: the analysis of the sample begins. The AC is iteratively updated as needed as the investigation progresses.
5. Conclusion: the results of the close reading are written, and some final considerations are established.

FIGURE 20 – METHOD CLOSE READING



SOURCE: the author, based on Fadel (2020)

Additionally, the framework proposed by Von Engelhardt (2002) was used to analyze the visual language, alongside a method proposed by the author. This visual analysis was done simultaneously with the Close Reading. According to Von Engelhardt, the researcher must:

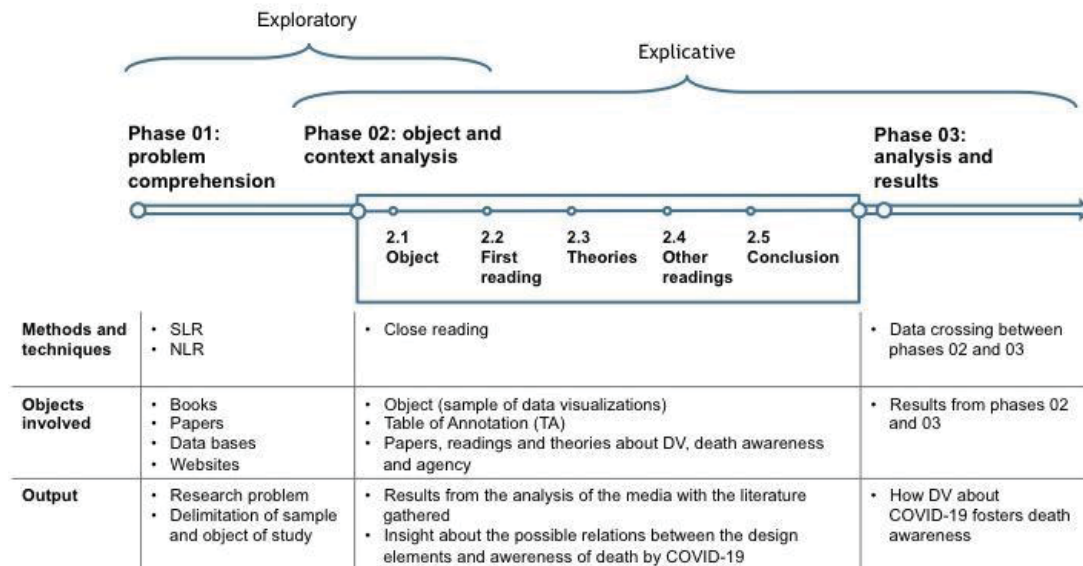
1. Briefly describe the object to be analyzed;
2. Make a note of the source;
3. Comment on the specific aspects that have drawn the researcher's interest;
4. Begin the analysis, which is subdivided into:
 - 4.1 Syntax of spatial structure
 - 4.2 Type of correspondence
 - 4.3 Type of graphic representation

Close Reading of the media allows the researcher to draw connections between the elements present in the sample of DV and the potential ways the interactor is involved with the object.

The third phase qualitatively analyzed the data collected in the previous stages and compared the results. Results from the Close Reading were cross-referenced with the results from phase 02 to conclude the

connections between design elements and COVID-19 death awareness. All of the phases are summarized in figure 21.

FIGURE 21 – DESCRIPTIVE DIAGRAM OF METHOD



SOURCE: the author

The following section describes the materials used for the analysis of the sample. It focuses on the annotation chart constructed iteratively during Close Reading.

7.2 MATERIALS AND METHODS

An annotation chart (AC) was created to analyze the sample of DV, as per the Close Reading method (CHART 3). The chart was based on the theories gathered in chapters 2–5. The annotation chart (AC) was divided into four categories: syntactic, semantic, classification of graphic representation, and engagement elements. It followed the discussions of visual language in chapters 2 and 3 and the framework proposed by von Engelhardt (2002). This annotation chart was then modified during the analysis and served as the basis for the creation of the framework presented in this dissertation, which was the main goal of this project.

The sample of DV was analyzed using the criteria described in the AC explained in this chapter. Next, the selection and gathering criteria of artifacts are discussed.

7.3 SAMPLING PROCEDURE

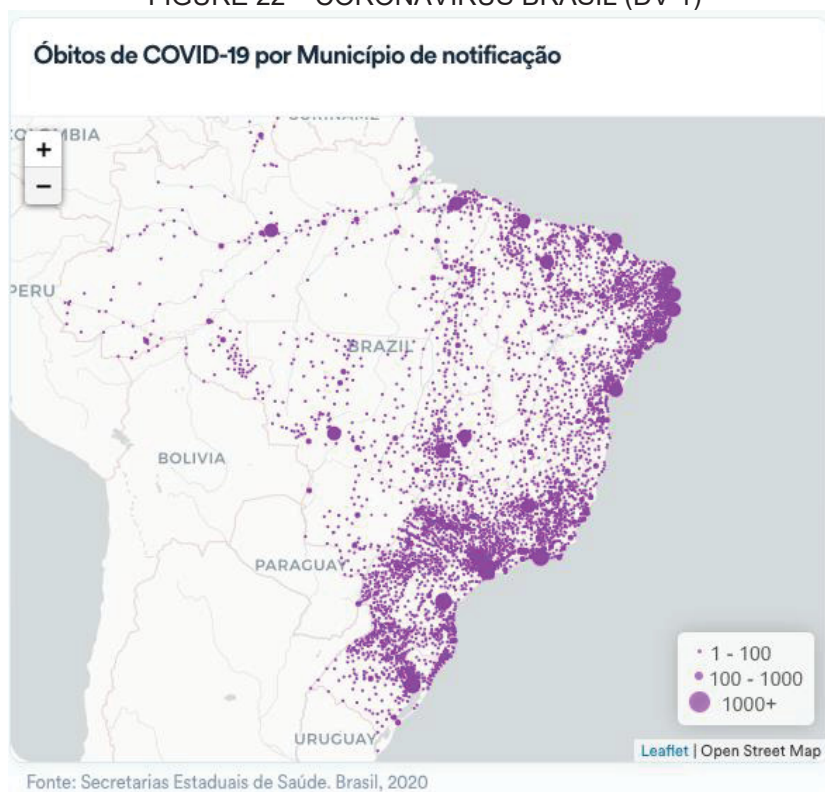
There were five primary considerations when selecting the sample. The first one was to choose data visualizations from popular and well-known dashboards. The second was to choose DV hosted on public websites that were easily accessible and DV that dealt with death, specifically. The fourth consideration was to choose both DVs that were used globally and those particular to the situation in Brazil. The final criterion included any DV that differed from the sample average.

The sample had to follow all of these criteria, with the exception of the first one, if justified. If a DV were found that wildly different from the average sample, it would be included regardless of its popularity.

With these considerations in place, six websites were selected: Coronavírus Brasil, Portal de Transparência do Registro Civil, GYRO 4life, John Hopkins COVID-19 Dashboard, Google, and the WHO Dashboard. From each website were taken the most visually significant or emphasized DV. Each website had a different number of DVs available, so the sample did not consist of equal DVs from each website.

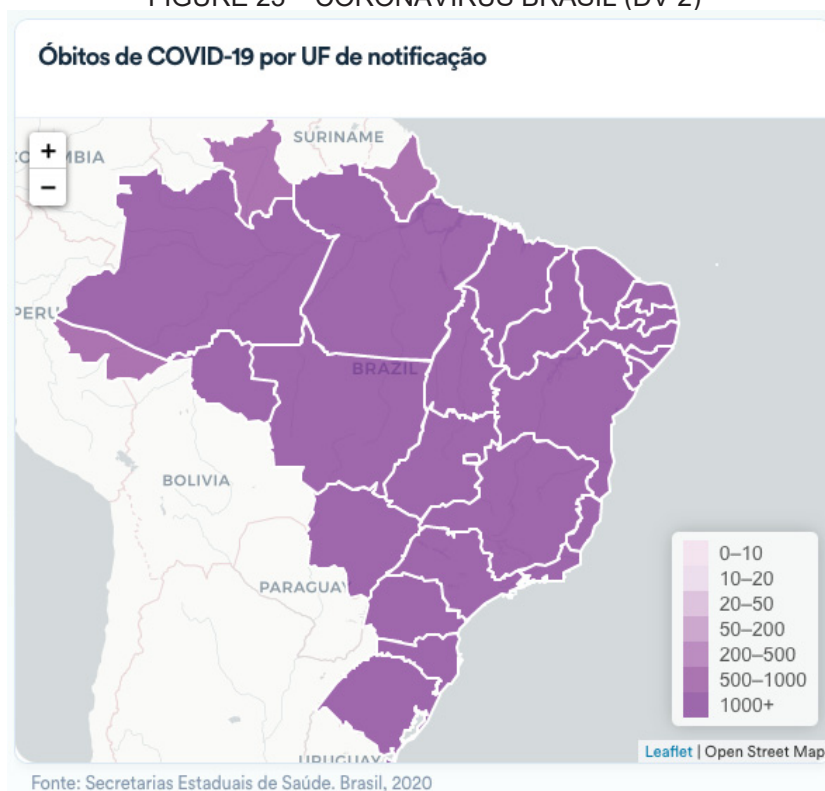
Coronavírus Brasil is a website operated by the Brazilian government and updated regularly to display the pandemic situation in Brazil. From this website were taken five DV. The sample can be found in figures 22–26.

FIGURE 22 – CORONAVÍRUS BRASIL (DV 1)



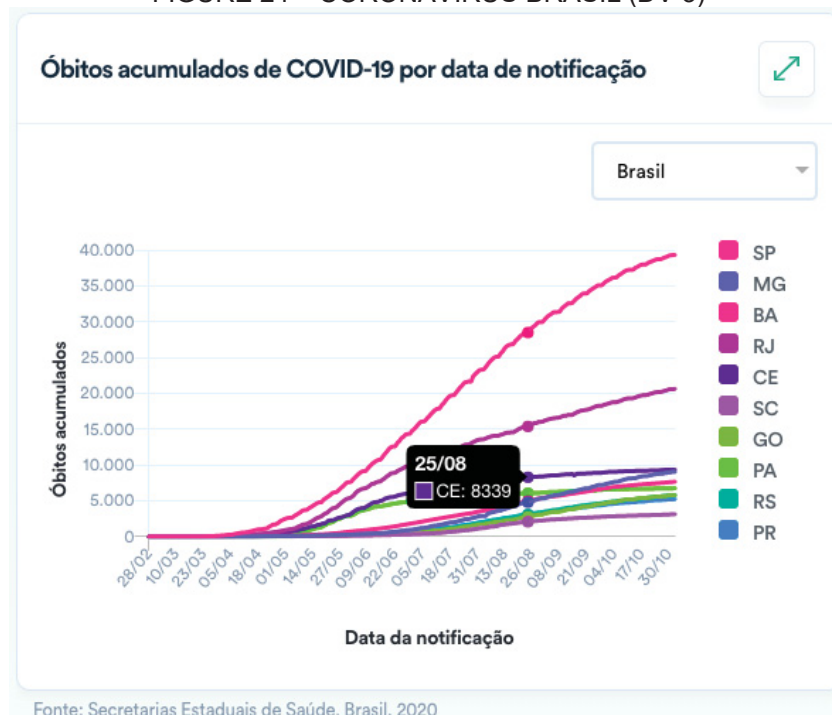
SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 24 September. 2020.

FIGURE 23 – CORONAVÍRUS BRASIL (DV 2)



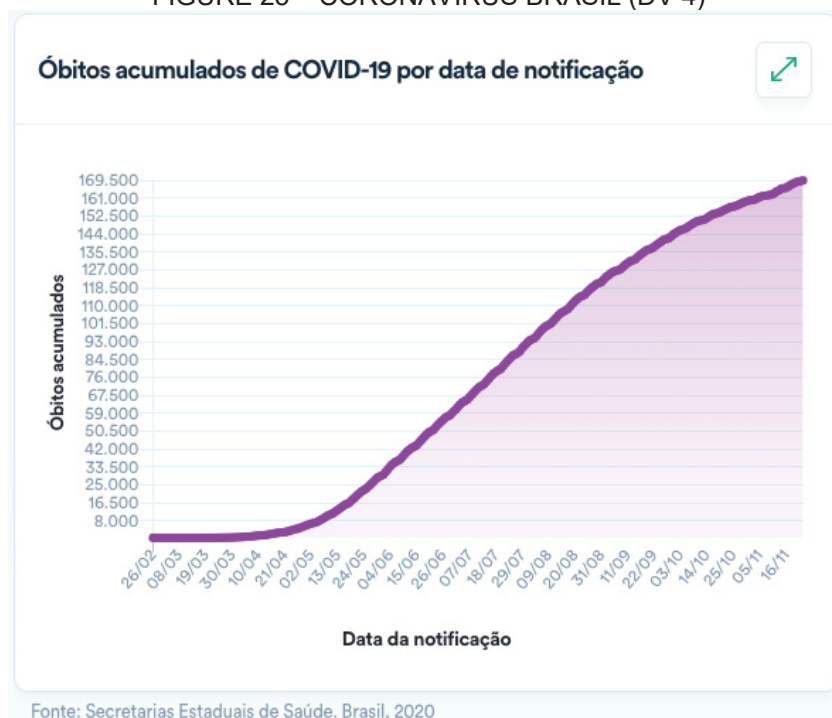
SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 24 September. 2020.

FIGURE 24 – CORONAVÍRUS BRASIL (DV 3)



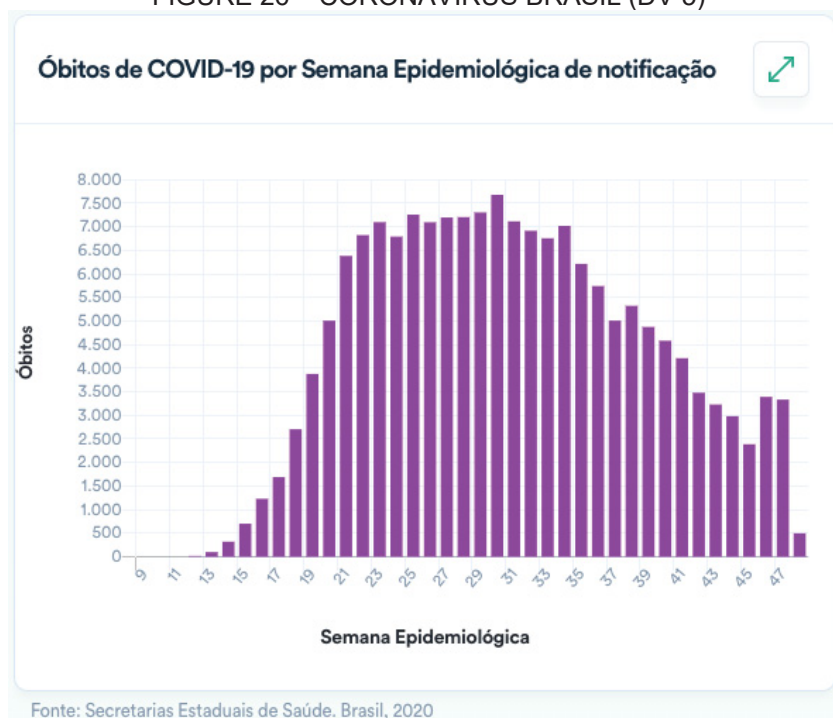
SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 24 September. 2020.

FIGURE 25 – CORONAVÍRUS BRASIL (DV 4)



SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 24 September. 2020.

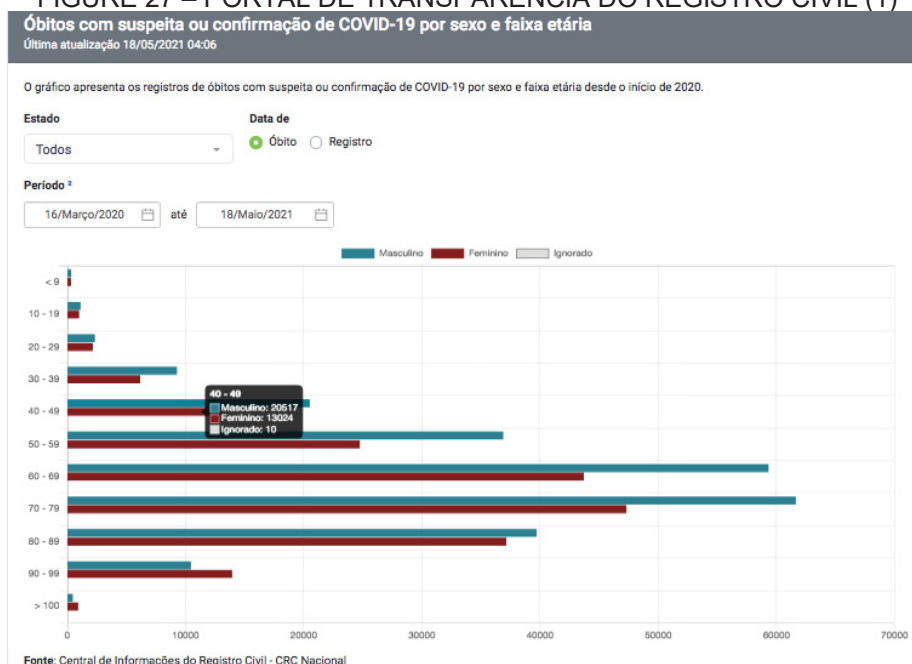
FIGURE 26 – CORONAVÍRUS BRASIL (DV 5)



SOURCE: Coronavírus Brasil. Available on: <<https://covid.saude.gov.br/>>. Accessed: 24 September. 2020.

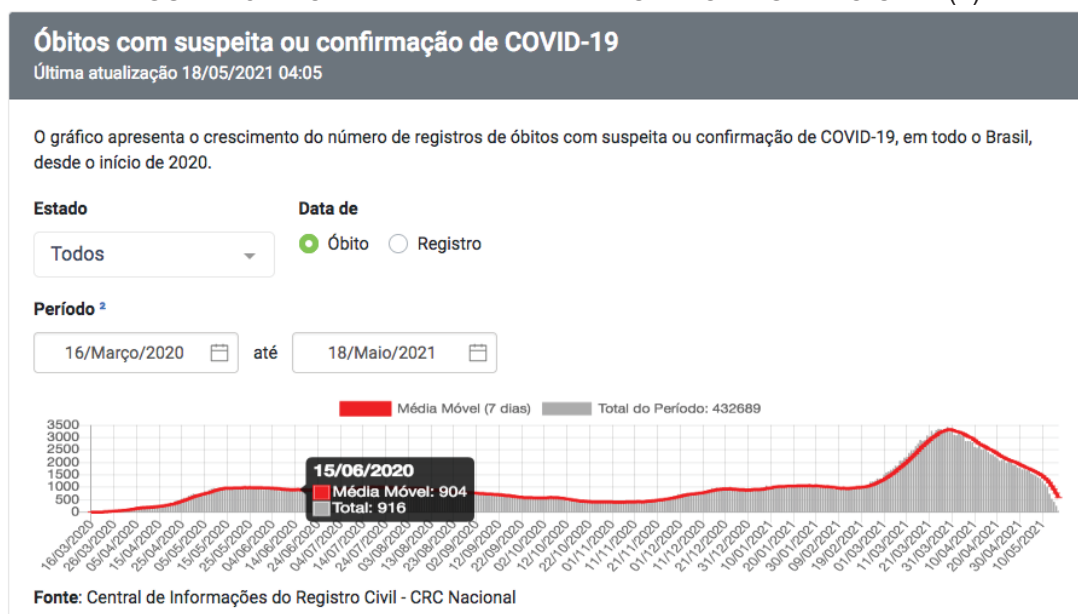
Portal de Transparência do Registro Civil is another website by the Brazilian government. Two DVs were taken from this website, seen in figures 27 and 28.

FIGURE 27 – PORTAL DE TRANSPARÊNCIA DO REGISTRO CIVIL (1)



SOURCE: Portal de Transparência do Registro Civil. Available on: <<https://transparencia.registrocivil.org.br/especial-covid>>. Accessed: 18 May. 2021.

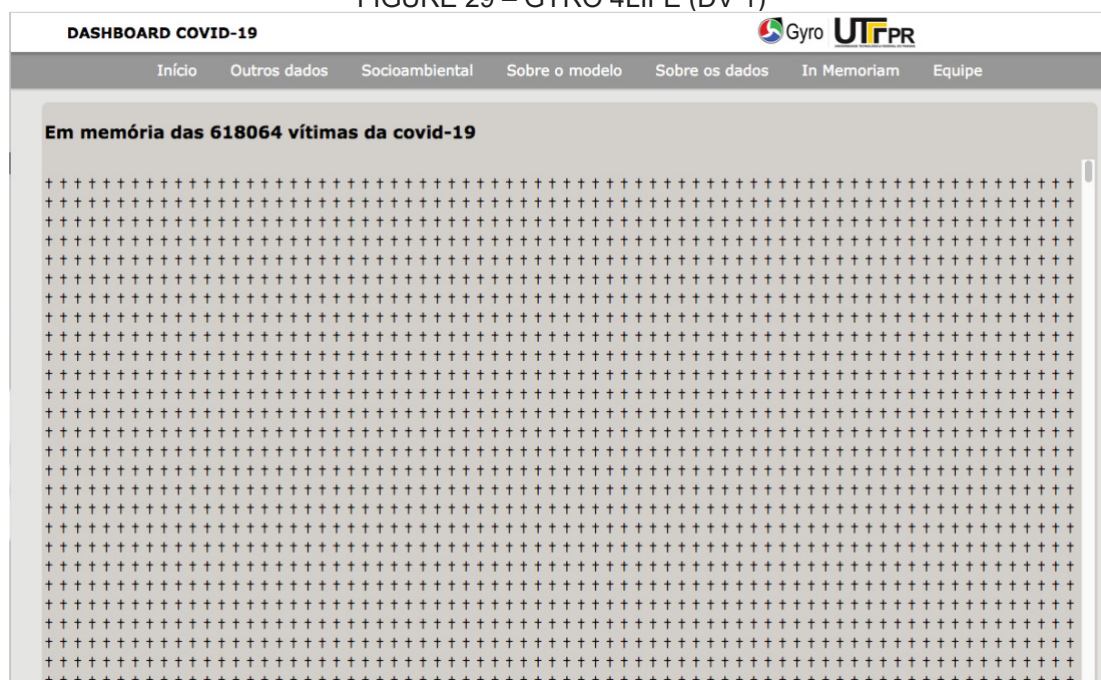
FIGURE 28 – PORTAL DE TRANSPARÊNCIA DO REGISTRO CIVIL (2)



SOURCE: Portal de Transparência do Registro Civil. Available on: <https://transparencia.registrocivil.org.br/especial-covid>. Accessed: 18 May. 2021.

A research group called GYRO from the Federal Technological University of Paraná (UTFPR) created and ran the GYRO 4life. The website is divided into sections. The one chosen was 'In Memorial,' which only had one DV that occupied the entire screen. The screenshot can be found in figure 29.

FIGURE 29 – GYRO 4LIFE (DV 1)



SOURCE: GYRO 4life. Available on: https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NgvW-FgrnHmVvFCitiANyYSmlWBXEO_m6-M857sOgykg#. Accessed: 20 December. 2021.

The website COVID-19 Dashboard by John Hopkins was the first to create a dashboard for monitoring the pandemic that could be upgraded in real-time (COMBA, 2020). The website only has two kinds of data visualization, and both were chosen. They can be seen in figures 30 and 31.

FIGURE 30 – JHU COVID-19 DASHBOARD (DV 1)



SOURCE: JHU COVID-19 Dashboard. Available on: <<https://coronavirus.jhu.edu/map.html>>. Accessed: 18 May. 2021.

FIGURE 31 – JHU COVID-19 DASHBOARD (DV 2)



SOURCE: JHU COVID-19 Dashboard. Available on: <<https://coronavirus.jhu.edu/map.html>>. Accessed: 18 May. 2021.

Google presents two DVs as the first results when one searches for 'COVID-19'². Because it is so available and disseminated globally, those two visualizations were added to the sample. Google uses location to determine what visualization it should show the interactor, so the DV presented here is specifically about the state of the pandemic in Brazil. The DVs can be found in figures 32 and 33.

² Valid on June 6th 2021, with the keywords 'COVID-19', 'COVID', 'corona', and 'coronavirus'

monitor and present data about cases, deaths, and now vaccinations. The DVs chosen from this website are in figures 34–37.

FIGURE 34 – WHO DASHBOARD (DV 1)



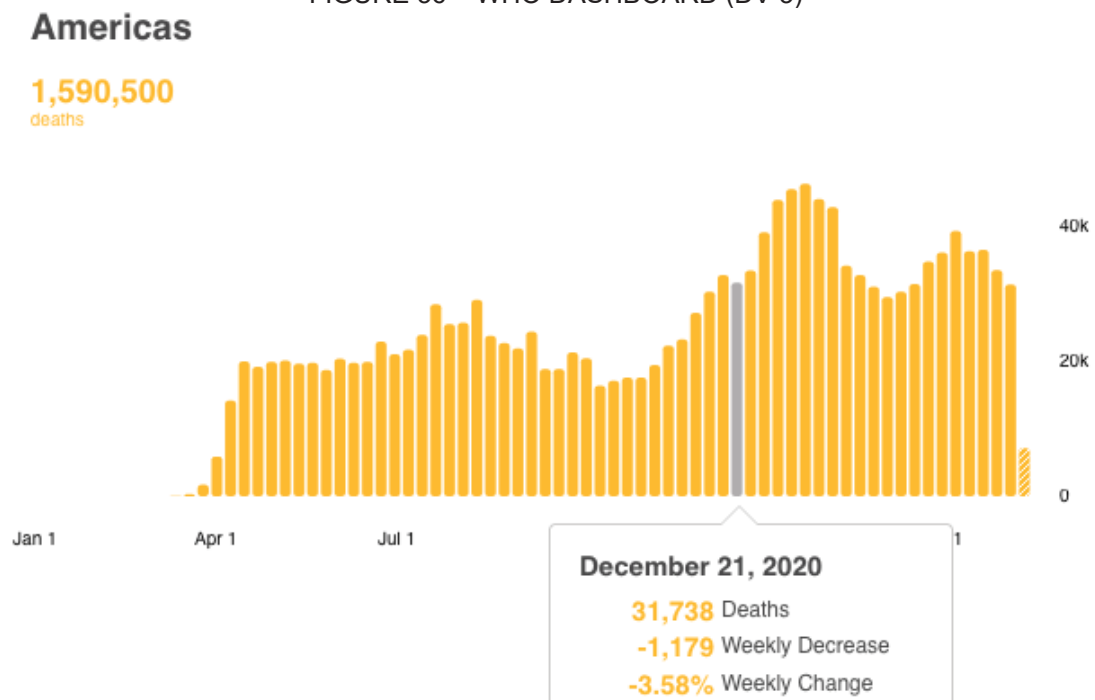
SOURCE: WHO Dashboard. Available on: <<https://covid19.who.int/>>. Accessed: 18 May. 2021.

FIGURE 35 – WHO DASHBOARD (DV 2)



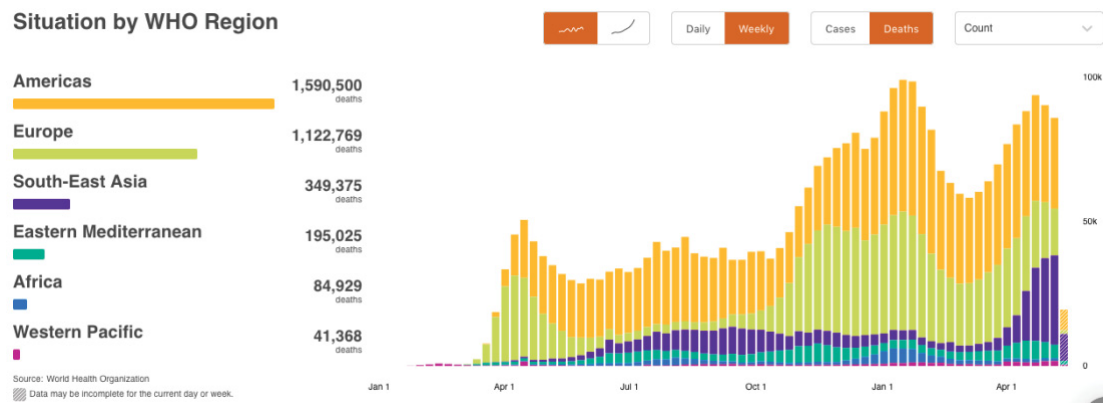
SOURCE: WHO Dashboard. Available on: <<https://covid19.who.int/>>. Accessed: 18 May. 2021.

FIGURE 36 – WHO DASHBOARD (DV 3)



SOURCE: WHO Dashboard. Available on: <<https://covid19.who.int/>>. Accessed: 18 May. 2021.

FIGURE 37 – WHO DASHBOARD (DV 4)



SOURCE: WHO Dashboard. Available on: <https://covid19.who.int/>. Accessed: 18 May, 2021.

In total, sixteen DVs were pre-selected to be part of the sample. Upon a preliminary analysis of the sample, three categories were identified: statistical map, statistical time chart, and statistical chart (VON ENGELHARDT, 2002). The DVs shown in figures 22, 23, 31, 33, and 34 are statistical maps, while the ones that appear in figures 24-28, 30, 32, 35-37 are statistical time charts, and lastly the DV in figure 29 is a statistical chart. Because Close Reading requires the researcher to spend time analyzing a piece of media, one DV from each category was selected to go through in-depth analysis. Therefore, the sample went from 16 data visualizations to 3 DV that were representative.

For each of the three categories one DV was chosen. For the statistical map, the DV analyzed was the JHU map (figure 31), for the statistical time chart, it was chosen to analyze the Google DV (figure 32). The JHU map was chosen for being the first tracking dashboard for the COVID-19 pandemic, and Google was chosen for its high visibility. For the statistical chart, there was only one DV, which was the one analyzed (figure 29).

8 RESULTS

The results presented in this chapter fulfill the second specific objective of this dissertation by describing the graphic elements used to represent death by COVID-19. The chapter is divided into four sections. The first section focuses on the main contribution of this project, the analysis framework. The following sections show the results of using that framework to analyze the three data visualization. First come the JHU data visualization, then the Google DV and finally the GYRO data visualization. Because of the complexity of each data visualization, the results get progressively shorter. John Hopkins University has the most complex DV compared to the other two, so its section spans longer.

8.1 THE FRAMEWORK (SSCE)

The framework was named SSCE for Semantic, Syntactic, Classification, and Elements of engagement. It was the main contribution of this work and the answer to the main objective. It was constructed based on the theories of Von Engelhardt (2002), Weber (2020), and Börner et al. (2019). Then, through an iterative process between analyzing the three visualizations, the SSCE framework was further edited to better suit its purpose of assisting designers to describe and analyze visual elements of data visualizations and their relations with death awareness.

The complete SSCE framework can be found in CHART 6 and will be further explained in the coming sections. This chapter is separated into five sections, each one which will correspond to a section of the SSCE framework: basic description, syntactic, semantic, classification of graphic representations, elements of engagement.

CHART 6 – COMPLETE FRAMEWORK (SSCE)

Description of the data visualization	
Source	
Characteristic that the researcher chooses to highlight	
SYNTATIC	
Composite syntactic structures	

Simultaneous combination Nesting	Background inset		
	Multi-panel display	Graphic multiple Shared-axis multi-panel	
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation	
	Area-fill attributes	Value Grain Color	
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition	
	Object-to-space	Metric space Distorted metric space	
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier	
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Gridlines	
	No anchoring		
SEMANTIC			
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional		
Mode of expression	Pictorial Non-pictorial		
Informational roles	Information objects		
	Reference objects	Spatial objects	
		Legend objects	
	Decoration objects		
Interactions	Zoom Search and locate Filter Details on demand History Extract Link and brush Projection Distortion		

CLASSIFICATION OF GRAPHIC REPRESENTATIONS		
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network	
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram	
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	
Data scales	Nominal Ordinal Interval Ratio	
Analysis	Statistical Temporal Geospatial Topical Relational	
ELEMENTS OF ENGAGEMENT		
Storytelling	Narrator	
	Tellability	
	Sequentially	
	Temporal dimension	
Perspective shifting		

Source: the author

8.1.1 Basic description

The first section of the SSCE framework aims to make the designer describe the visualization and make a note of the source. Then, it asks the design to do a preliminary read of the artifact and make note of what

characteristics were most striking. This serves the purpose of making the designer think about what elements will be in focus during the analysis to guide it. CHART 7 shows this section of the SSCE framework.

CHART 7 – SSCE FRAMEWORK: BASIC DESCRIPTION

Description of the data visualization	
Source	
Characteristic that the researcher chooses to highlight	

Source: the author

8.1.2 Syntactic

The second section of the SSCE framework deals with the syntactic of the data visualization. In this section the designer will assess the many ways in which composite syntactic structures are formed. First, we can have a simultaneous combination, or nesting. This can happen either with a background inset – i.e., when one image is superimposed onto the other, or a multipanel display – i.e., when there are multiple images next to one another.

The second row pertains to the visual attributes that are given to graphic objects. Those are divided into spatial attributes (like the shape and size of an element), or the area-fill attributes (such as what color and texture the element has).

After this the syntactic structures are to be noted by the designer. These are the relationships that happened between the graphic object that were described previously. They are separated into object-to-object and object-to-space. The former talks about the many types of relationships that can happen between two objects, while the second talks about the relationships an object can have with the space it resides in.

Lastly, the final row talks about the syntactic roles of the graphic objects mentioned above. They are divided into three types of anchoring. The first one is about anchoring an object to another object, for example when a container is used to separate objects. The second type is when an object is anchored to a specific space, like the symbol of location on google maps. The last type of anchoring is when an object is not anchored to anything. CHART 8 shows this part of the SSCE framework.

CHART 8 – SSCE FRAMEWORK, SYNTACTIC

SYNTACTIC			
Composite syntactic structures			
Simultaneous combination Nesting	Background inset		
	Multi-panel display	Graphic multiple Shared-axis multi-panel	
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation	
	Area-fill attributes	Value Grain Color	
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition	
	Object-to-space	Metric space Distorted metric space	
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier	
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Gridlines	
	No anchoring		

Source: the author

8.1.3 Semantic

The third part of the SSCE framework talks about the semantics of a data visualization. It is divided into four rows. The first one allows the designer to map out the types of correspondence a graphic element has. For example, a graphic element could communicate information to the interactor through literal correspondence, which would be the drawing of a tree to mean a tree. Additionally, it could use metaphors to generate meaning, as well as

metonyms, rebus, or arbitrary conventional. These elements were explained in more detail on chapter 3.1.

The second-row talks about the two modes of expression, pictorial or non-pictorial. Pictorial would be any image, regardless of how realistic they look. This ranges from photos all the way to icons. Non-pictorial, on the other hand, are elements like words.

Next comes the information roles of the graphic objects. An object can serve the purpose of directly passing on information to the user, serving as a reference for the interactor to better absorb the information, or be there as a decoration.

Lastly, the SSCE framework allows the designer to categorize the kinds of interactions that the data visualization lets the interactor make. They can be zoom features, filters, search engines and more. All these elements were further explained in chapter 3.1. CHART 9 shows this part of the SSCE framework.

CHART 9 – SSCE FRAMEWORK, SEMANTIC

SEMANTIC		
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional	
Mode of expression	Pictorial Non-pictorial	
Informational roles	Information objects	
	Reference objects	Spatial objects
		Legend objects
	Decoration objects	
Interactions	Zoom Search and locate Filter Details on demand History Extract Link and brush Projection Distortion	

Source: the author

8.1.4 Classification of graphic representations

This part of the SSCE framework pertains to the types of graphic representation, and which one best fits the data visualizations being analyzed.

The first two rows map out the kinds of representation that exist. The primaries are the simplest forms of data visualization, which then can be combined to form the hybrid data visualization.

Next the SSCE framework separates data visualization into the type of insight that they need to give the users. For example, if the visualization has the insight need to give the interactor geospatial notion, then it probably will mean that it will be classified as a map and employ syntactic and semantic elements that refer to physical space.

The fourth-row deals with the types of data scale that the data visualization can have, and the last row refers to the type of analysis that was done to that data. For example, time charts will always have temporal analysis done to them. CHART 10 shows this part of the SSCE framework.

CHART 10 – SSCE FRAMEWORK, CLASSIFICATION OF GRAPHIC REPRESENTATIONS

CLASSIFICATION OF GRAPHIC REPRESENTATIONS		
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network	
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram	
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	

Data scales	Nominal Ordinal Interval Ratio	
Analysis	Statistical Temporal Geospatial Topical Relational	

Source: the author

8.1.5 Elements of engagement

The final part of the SSCE framework allows the designer to analyze the graphical elements that foster certain type so interactor engagement. It is divided into two elements, storytelling and perspective shifting. Storytelling pertains to the elements that might create a story that are embedded into the data visualization. Perspective shifting, on the other hand, talks about whether the visualization uses elements that cause the interactor to shift perspective and see the large scope of the data as well as the individual weight of each data point. CHART 11 shows this part of the SSCE framework.

CHART 11 – SSCE FRAMEWORK, ELEMENTS OF ENGAGEMENT

ELEMENTS OF ENGAGEMENT		
Storytelling	Narrator	
	Tellability	
	Sequentially	
	Temporal dimension	
Perspective shifting		

Source: the author

Next are the results of the analysis of the data visualizations that were done following the SSCE framework. This step sought to verify the consistency of the framework and refine it. First is the analysis of the data visualization in the John Hopkins University platform, followed by Google and Gyro UTFPR.

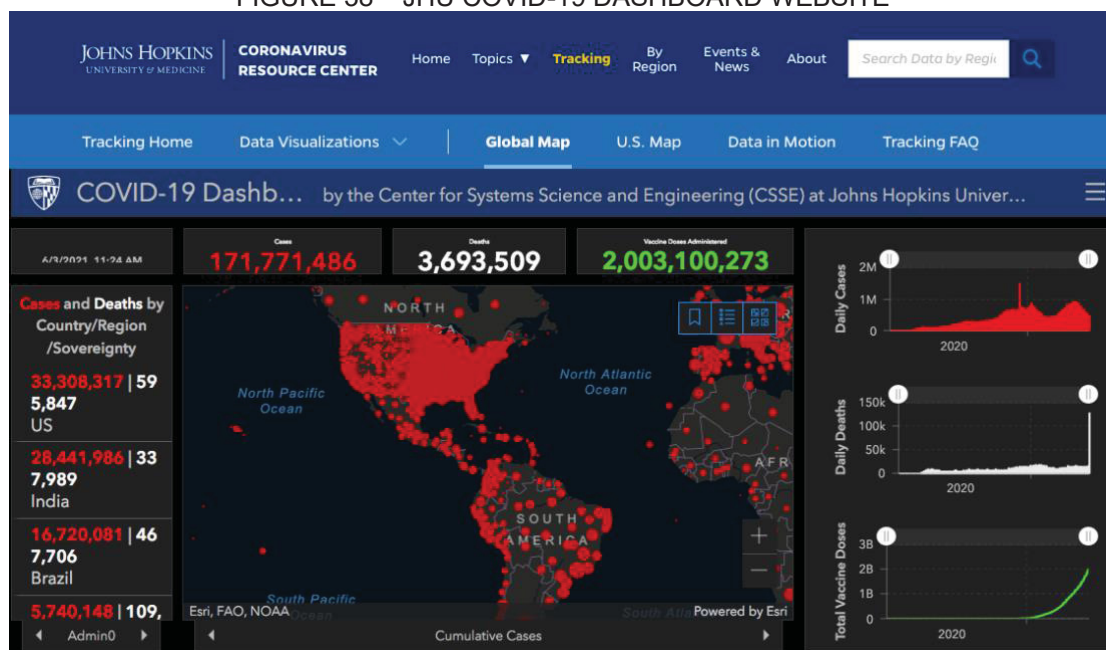
8.2 JOHN HOPKINS UNIVERSITY

John Hopkins University statistical map was the first DV analyzed, as well as the most complex of the three visualizations. It is an interactive map showing the number of deaths as red circles on top of geographical locations. The circle area corresponds to the number of deaths.

The DV is part of the JHU COVID-19 Dashboard website, alongside other DVs. The one chosen is in the middle of the webpage, framed on all sides by smaller DV. On top, there are three boxes, one for the number of cases (in red), one for the number of deaths (in white), and a final one for the number of vaccines (in green). The website has a black background, and the boxes where each of the DVs are placed are a slightly lighter color (dark gray).

Three bar graphs report the number of daily cases, death, and vaccine doses on the right side, with the same color-coding. There is a table with the number of deaths and cases by country/region on the left side. A screenshot of the webpage can be seen in figure 38.

FIGURE 38 – JHU COVID-19 DASHBOARD WEBSITE



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 03 June. 2021.

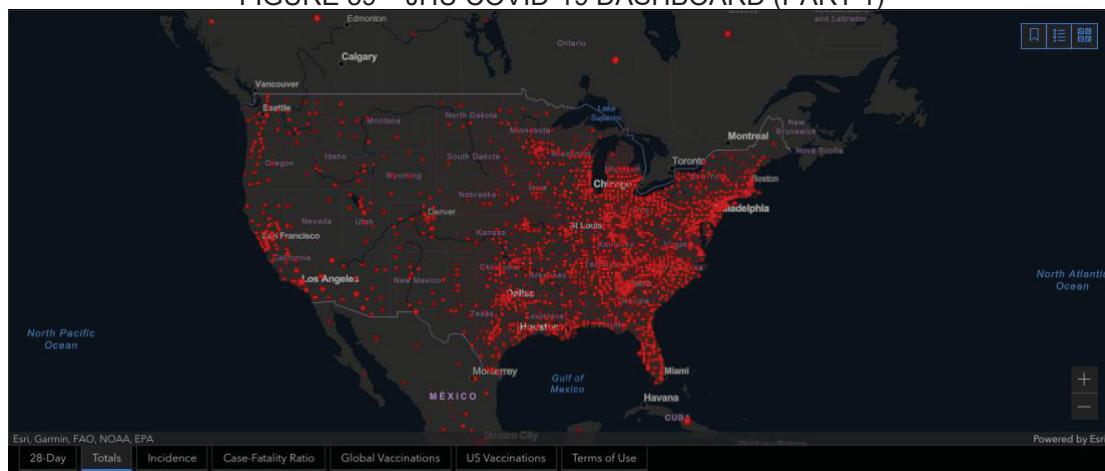
The DV in the center of the webpage is more significant, so it was chosen as the one to be analyzed. The website opens on the DV for

cumulative cases giving it the most emphasis out of everything on the webpage. Figures 39–41 show the DV for cumulative cases.

The map is colored a dark gray and has a background of very dark blue to represent the ocean. The only elements of color are the saturated red circles that represent the number of cases.

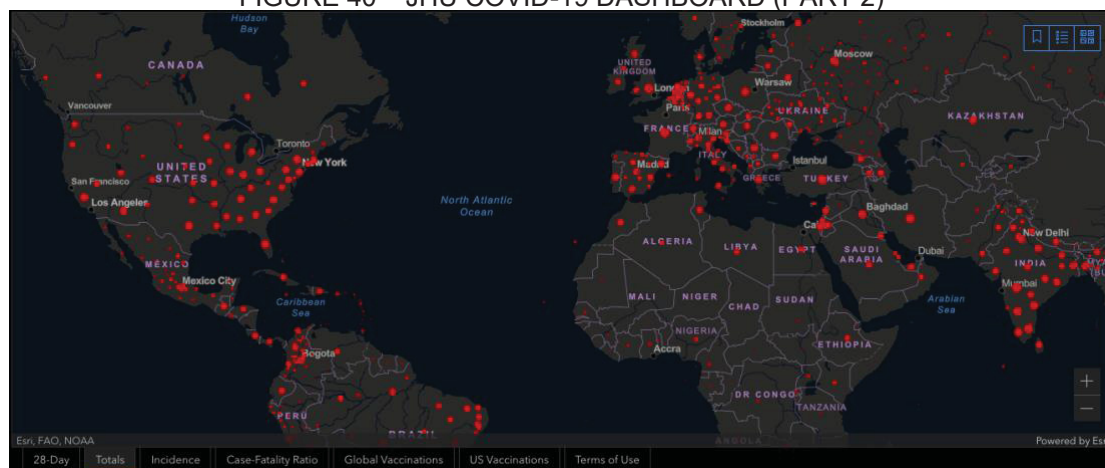
The DV has a few interactive options for the interactor. It lets the interactor zoom in to see the map in more detail (figure 39) or zoom out to see a global scale (figure 40). Additionally, to the zooming features, the interactor can click and drag the map and move it to different places.

FIGURE 39 – JHU COVID-19 DASHBOARD (PART 1)



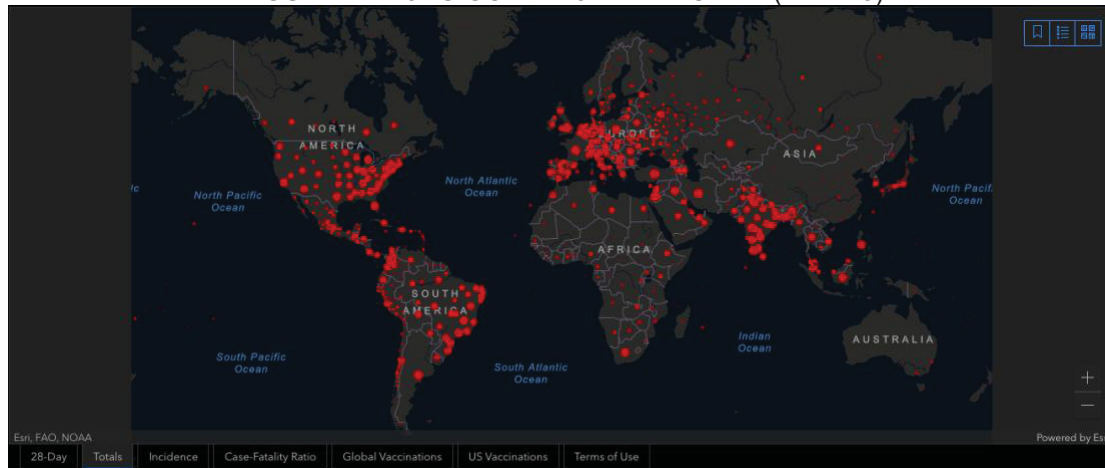
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 40 – JHU COVID-19 DASHBOARD (PART 2)



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 41 – JHU COVID-19 DASHBOARD (PART 3)

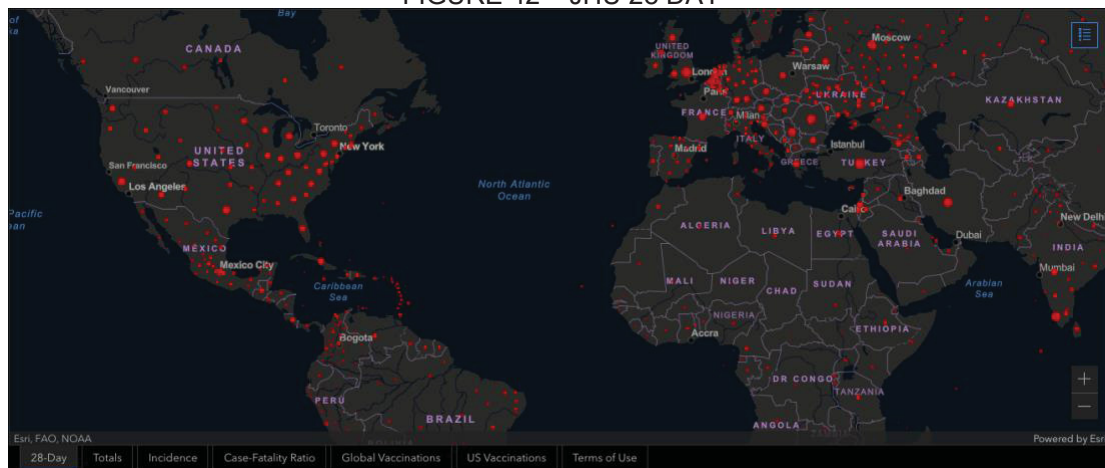


SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

There are six types of information in the DV, which can be selected through the tabs on the bottom of the page. They are: “28 Day” (figure 42), “Totals” (figure 41), “Incidence” (figure 43), “Case-Fatality Ratio” (figure 44), “Global Vaccinations” (figure 45), and “US Vaccinations” (figure 46).

The only element that differs between these six types of DV is the number and size of circles and their color: red for “28 Day” and “Totals,” yellow for “Incidence,” white for “Case-Fatality Ratio,” and green for “Global Vaccinations” and “US Vaccinations.”

FIGURE 42 – JHU 28 DAY



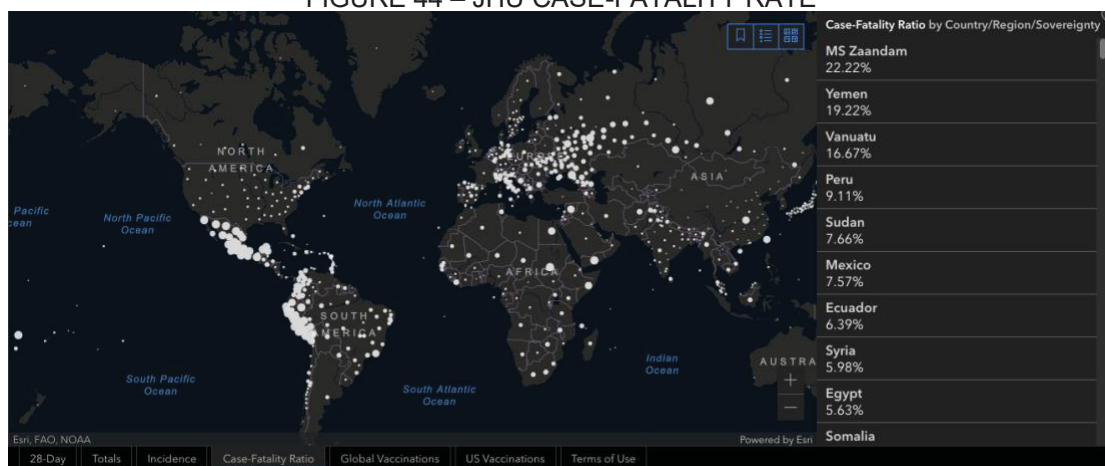
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 43 – JHU INCIDENCE



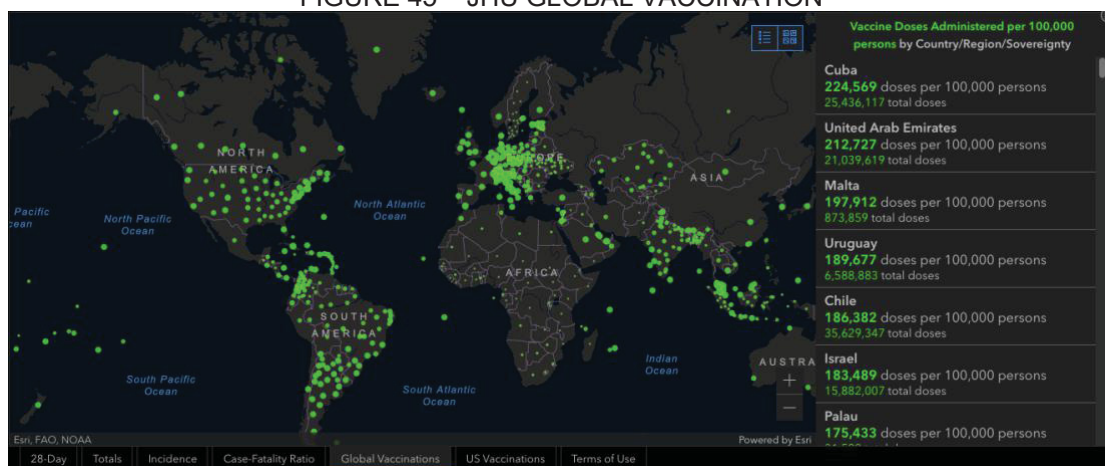
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 44 – JHU CASE-FATALITY RATE



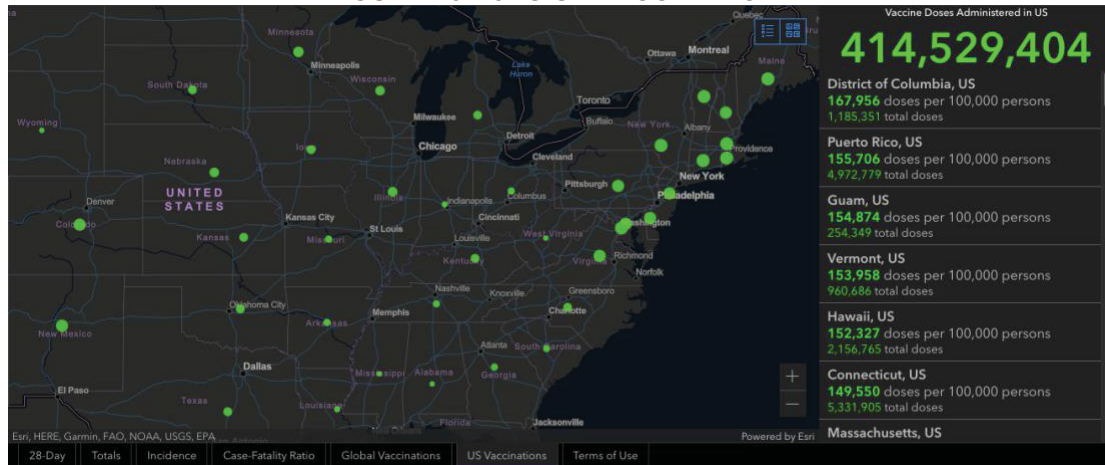
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 45 – JHU GLOBAL VACCINATION



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

FIGURE 46 – JHU US VACCINATIONS



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 28 May. 2021.

The process of analysis of the DV was guided by Close Reading, in which the object was experienced and used many times to understand how the elements highlighted on the Annotation Chart (AC) were used. Chart 12 shows the analysis of the DV using the AC.

CHART 12 – ANALYSIS OF THE JHU DATA VISUALIZATION

Description of the data visualization	Statistical map composed of four clusters. Map is a background inset, where there are two interfaces superimposed. First is a gray square with blue outline. It opens a legend window when clicked. Second, are the two boxes at the bottom right, which serve as zoom. The map is a dark gray, with light gray dividers. The ocean is dark blue with blue labels. Continents are labeled in light gray and as the zoom increases the names and borders of countries/states appear. The lines that establish borders are gray, the lines used for roads are light blue and the lines for rivers are dark blue, same color as oceans and lakes. Each location is marked with a different size red dot. The dots are smaller in places that have less infected and larger where there are more reported cases. Under all this is the fourth cluster, a tab menu where the interactor can select the type of information they want to see  The screenshot shows a world map with four clusters of data points highlighted in red. Cluster 1 is in North America, Cluster 2 is in Europe, Cluster 3 is in Africa, and Cluster 4 is in South America. The map is dark gray with light gray borders and labels. The ocean is dark blue with blue labels. The map is powered by Esri.
Source	John Hopkins University, https://coronavirus.jhu.edu/map.html last accessed: 20/09/2021
Characteristic that the researcher chooses to highlight	The color red The dark background The focus on the negative

	The mode of representation of a map with the red circles indicating contagion		
SYNTACTIC			
Composite syntactic structures			
Simultaneous combination Nesting	Background inset		This DV is a background inset, with a statistical map acting as the background. Two clusters are superimposed, one for legend and another for the zoom feature.
	Multi-panel display	Graphic multiple Shared-axis multi-panel	
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation	The red dots use size and spatial position to represent the degree of level of infection anchored to a specific location. Circles are the shape used to identify the number of cases.
	Area-fill attributes	Value Grain Color	Color is an area fill attribute, which acts as a metaphor, metonym, and arbitrary-conventional representation to signify danger.
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition	When the red dots grow too large and merge with the ones around them, there is spatial clustering, which creates a single visual element. Separation by separators is used with the empty space between the clusters of dots or between the red dots themselves. Superimposition happens in two instances. The first is the two clusters on the bottom and upper right. The second is the red dots superimposed on the map.
	Object-to-space	Metric space Distorted metric space	The DV uses distorted metric space., as well as metric space. This happens because the elements on the map have their meaning attached to their location.
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier	Labels are used for continents, countries, cities, oceans, lakes, and rivers.
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Gridlines	Line locators are the lines that divide countries and states. The red dots are point locators. They serve to anchor the number of infected to a geographical space. Surface locators are used for the position of lakes, or country delimitations
	No anchoring		n/a
SEMANTIC			
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional		The map and the real world have direct correspondence. Each country and continent on the map directly represent their real-world counterpart. The red color is a metaphor, metonym, and arbitrary-conventional correspondence. The metaphor is between red and dangerous things like fire and blood. Metonym comes from red being a visual element of, for example, blood. Arbitrary-conventional correspondence happens because red is often used when trying to

		warn people about danger (i.e., stop signs)
Mode of expression	Pictorial Non-pictorial	The map is pictorial, tracing a direct connection between reality and the DV. The red dots are non-pictorial and use different correspondences to pass the message of danger.
Informational roles	Information objects	The red dots serve to count the infections that happened in a day. When the data changes, the dots change with it.
	Reference objects	Spatial objects The lines for borders and bodies of water are reference objects for space., as well as the surface of the map.
		Legend objects Labels are used to identify places and bodies of water. There is an icon on the upper right corner that displays a legend explaining the red dots when clicked.
	Decoration objects	n/a
Interactions	Zoom Search and locate Filter Details on demand History Extract Link and brush Projection Distortion	The DV allows the interactor to zoom in and out and locate the map. It also has search and location functions that can be used to search for a specific geographical location. The filter can select only the countries of the type of information that the interactor wants to see, for example, choosing not to see information about vaccines and focusing on the number of cases.
CLASSIFICATION OF GRAPHIC REPRESENTATIONS		
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network	
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram	The DV is a statistical map, since it combines the data from statistical charts with specific geographical locations.
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	The DV's insight onto the interactor is the geospatial comparison between different geographical locations and their COVID-19 data.

Data scales	Nominal Ordinal Interval Ratio	The data presented in the DV is a ratio, as the distance between one data point and another is clear (i.e., one death, one contamination, one vaccine), and the zero point is not arbitrary (in this case, the zero point is no vaccines administered, or no deaths/contaminations)
Analysis	Statistical Temporal Geospatial Topical Relational	The analysis for the DV is focused on geospatial, as it seeks to show the differences in data across different geographical locations.
ELEMENTS OF ENGAGEMENT		
Storytelling	Narrator	Narration can happen as the interactor interacts with the DV. By zooming in or out of the DV, or click and dragging the map, the interactor creates their own narrative structure through scroll telling. When zooming in from the global view to more specific location, and vice-versa, individuality is fostered. When the interactor positions themselves inside the map through geographical location, a narrative of 'me against the rest' can be encouraged.
	Tellability	Tellability can only be fully assessed through interactor testing. However, there are design elements that can foster it for the interactor. The relevant nature of the DV makes it have a natural tellability, as it pertains to the lives of everyone. However, few elements emphasize the proper content of the data precisely because the representation presents data with minimal emotional impact. The contrast between the colors black and red are the only elements that supports emotion. Additionally, scale might come to add emotion to the visualization since seeing countries covered in red might incite feelings of fear.
	Sequentially	Few elements in the DV foster sequentiality. The representation only shows the world, as it is. There is no future that can be gleamed from it. However, because the DV changes periodically as more data is collected, it creates a sequence as the interactors go from one day to another. For each day (or sometimes couple of days), data will have changed, as will the red dots that represent it. Every time the DV is updated with new insights about the pandemic, the interactor can see the growth of the pandemic. Because of this, there is some sequence to the DV.
	Temporal dimension	Similar to sequentiality, time is frozen in the DV, but because of the constant updates, the interactor can get a sense of the passage of time if they see the DV for two

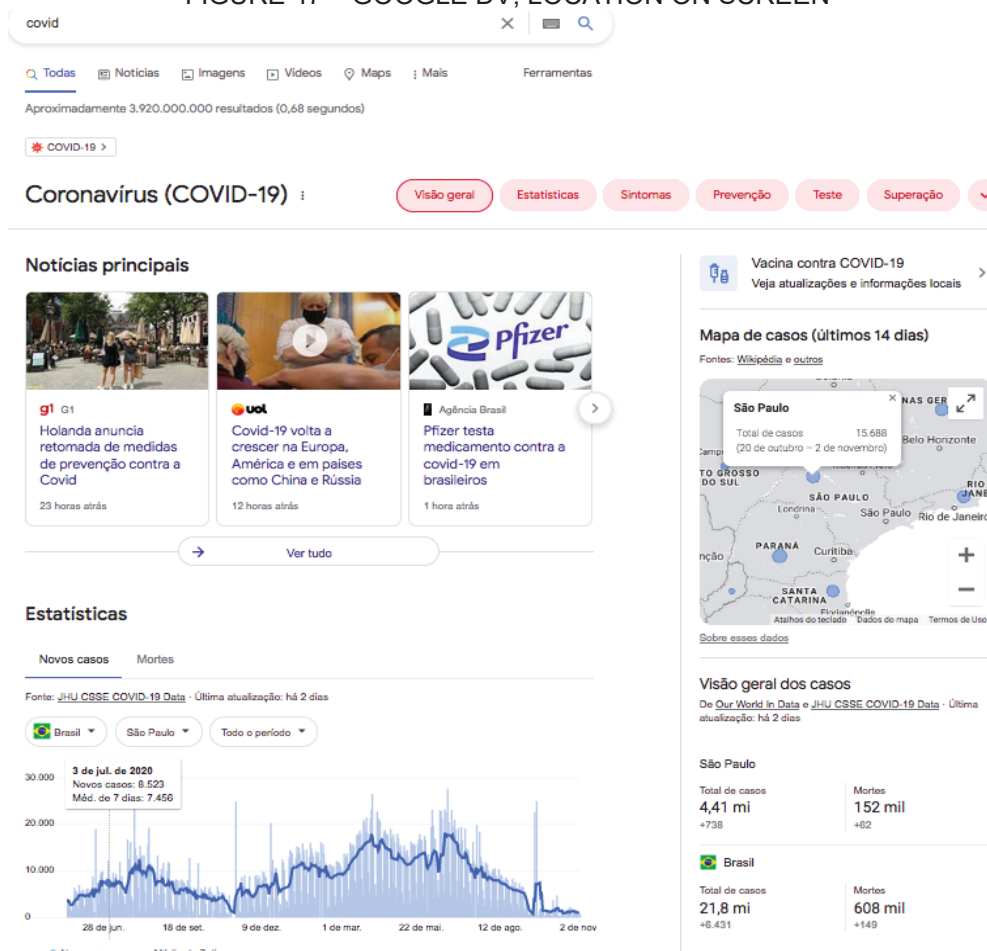
		or more days.
Perspective shifting		There is no perspective change for this DV. Even when the interactor zooms in closer, the information stays the same, just in a different scale. There is no moment when the close ups show the weight of death.

SOURCE: the author

8.3 GOOGLE

The statistical time chart hosted on Google was the second DV analyzed (figure 47). This DV appears whenever someone types in the words “COVID-19”, “COVID,” “corona,” “coronavirus,” or “SARS-COV” on the Google search bar³.

FIGURE 47 – GOOGLE DV, LOCATION ON SCREEN



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google⁴. Accessed: 03 Nov. 2021.

³ Valid on November 3rd 2021

⁴ All images from Google come from the link:
<<https://www.google.com/search?q=covid&client=firefox-b->

The DV appears on the main Google page, under a title card that reads “Coronavírus (COVID-19) with seven buttons to the right. The buttons are labeled: “visão geral,” “estatísticas,” “sintomas,” “prevenção,” “teste,” “superação” and the final one has a downward arrow that when clicked will expand that session to have three more buttons labeled: “variáveis,” “tratamentos”, and “notícias.”

To the right of the screen, there is another DV, a statistical map that shows the incidences of the virus based on the interactor’s location. This DV will not be analyzed, as the JHU already represents the sample for statistical maps.

Under the section for the main news is the DV that will be analyzed. The position of the DV in the Google page can be seen in figure 47, while the DV is in figure 48.

The DV has a title on the upper left corner named “Estatísticas” (“Statistics”). Below the title, there are two buttons, one for the new cases and one for the number of dead. Under those buttons, there is a text line explaining that the data that powers this DV came from the JHU CSSE COVID-19 dashboard and dates when the last update was made.

The three drop-down menus encased in light gray oval enclosures are related to place and period. The first menu allows the interactor to select the country they seek to view. It defaults to the country Google detects the interactor is in, but it can be manually changed. The button to select the country has the flag and the name of the country (figure 49). It is also possible to choose a global view of the pandemic instead of focusing on a particular place.

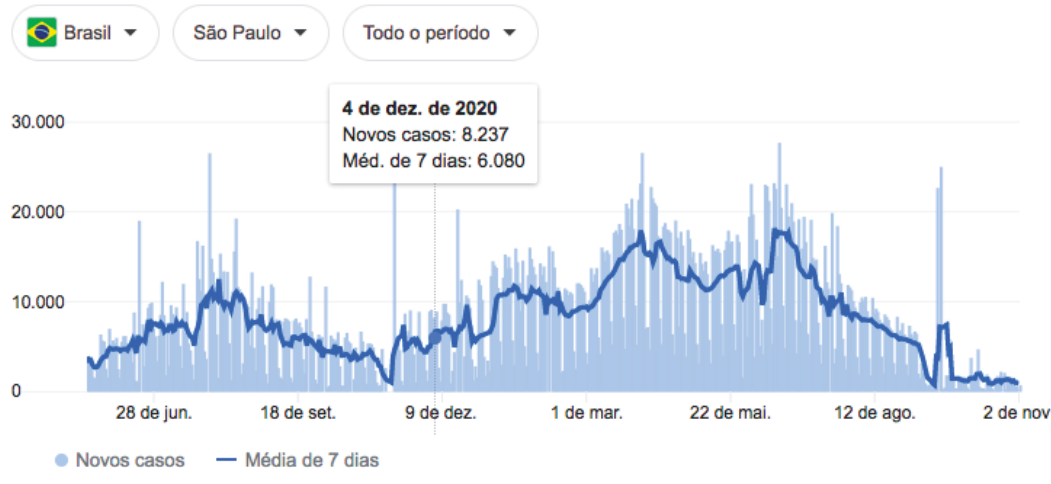
d&ei=wOmCYbiNBqQ85OUPiYWIOAk&oq=covid&gs_lcp=Cgdnd3Mtd2I6EAMyBwgAEMkDE
EMyBQgAEJIDMgglABCABBCxAziKCAAQsQMqgwEQQzILCAAQgAQQsQMqgwEyBAGAE
EMyBAGAEEMyCwgAEIAEELEDEIMBMgQIABBDmgsIABCABBCxAxCDAToHCAAQRxCwA
zoHCAAQsAMQqzoQCC4QxwEQowIQyAMQsAMQqzoQCC4QxwEQ0QMqyAMQsAMQqz
oKCC4QxwEQ0QMqzoKCC4QxwEQowIQQzoLCC4QgAQQsQMqgwE6CAguEIAEELEDO
g4ILhCABBCxAxDHARCjAjoHCAAQsQMqzoNCC4QsQMqgwEQowIQQ0oFCDgSATFKB
AhBGABQnRZYoBlgrxpoA3ACeACAAYkBiAHWBjIBAzEuNJgBAKABAcgBC8ABAQ&scient
=gws-wiz&ved=0ahUKEwi47f2Z_fzzAhUjHrkGHYkCApoQ4dUDCA0&uact=5>.

FIGURE 48 – GOOGLE DV

Estatísticas

Novos casos Mortes

Fonte: [JHU CSSE COVID-19 Data](#) · Última atualização: há 2 dias



A cada dia novos casos informados desde o dia anterior são mostrados · [Sobre esses dados](#)

SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 03 Nov. 2021.

FIGURE 49 – GOOGLE COUNTRY CHOICE



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

To the right side of the button to select countries, the interactor can choose the city (figure 53) and the period they wish to see (figure 54). The period can either be the entire pandemic since the beginning on May 21st, 2020 (figure 48), a week (figure 50), two weeks (figure 51), or thirty days (figure 52). The difference between them is the scope of the graph and the size of the bar graphs. The less period the chart covers, the wider the bars.

FIGURE 50 – GOOGLE, PERIOD OF 1 WEEK



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

FIGURE 51 – GOOGLE, PERIOD OF 2 WEEKS



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

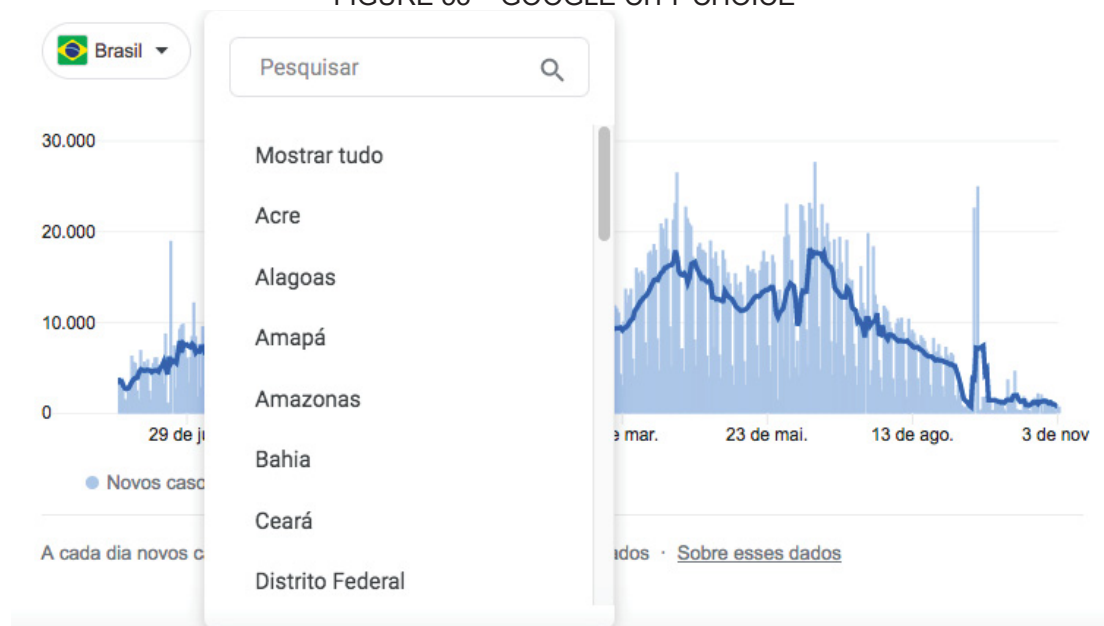
FIGURE 52 – GOOGLE, PERIOD OF 30 DAYS



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

Below these filtering buttons, there is the statistical graph. The chart's background is white, with faint light gray lines indicating horizontal sections. The X-axis shows the numbers of new cases, while the Y-axis shows the dates those cases were recorded. The graph is a mixed bar graph with a superimposed line graph. The bar graph is light blue, while the line graph is dark blue. Under the graph, there is a minor legend explaining what the chart's colors mean.

FIGURE 53 – GOOGLE CITY CHOICE



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

FIGURE 54 – GOOGLE PERIOD CHOICE



A cada dia novos casos informados desde o dia anterior são mostrados · [Sobre esses dados](#)

SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

The interactor can hover their mouse over specific points in the graph, and a little pop-up box will appear. When this happens, a light gray vertical dotted line seems to signify the mouse's location. The line graph will also show a blue circle for the Y position of the mouse. The box that pops up comes with information on the specific date the mouse is hovering over, the number of new cases for that day, and the average of 7 days assigned to that date (figure 55).

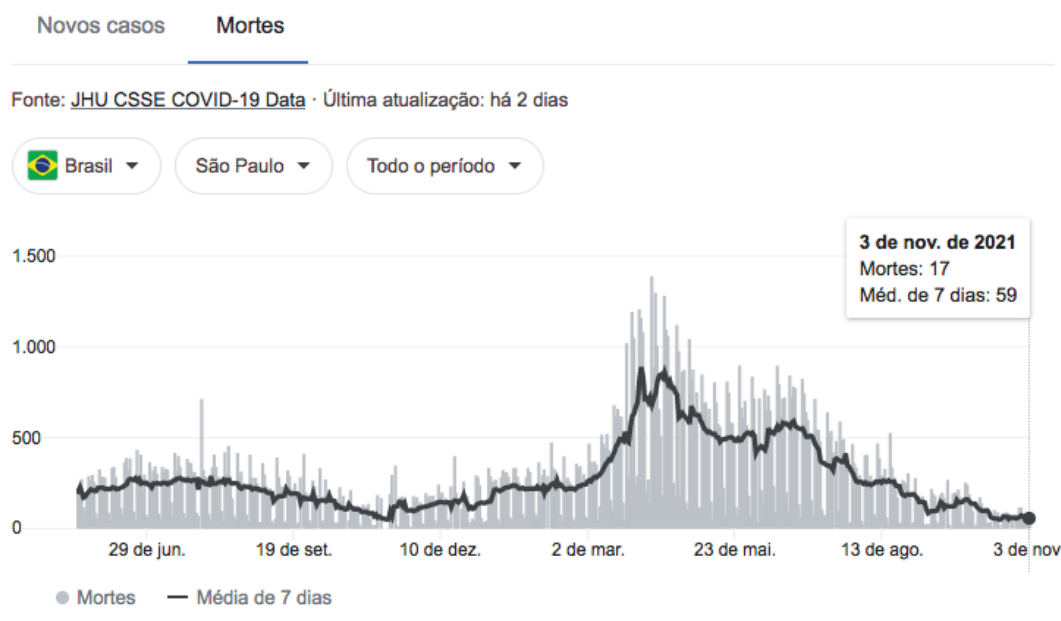
FIGURE 55 – GOOGLE POP-UP BOX



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

The DV has a second version depicting the number of the dead instead of the cases (figure 56). The only difference between the two is the color scheme. The DV depicting death uses light gray and black for the bar graph and line graph. The visual analysis of this DV follows on CHART 13.

FIGURE 56 – GOOGLE DV FOR DEATHS



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

CHART 13 – ANALYSIS OF THE GOOGLE DV

Description of the data visualization	The visualization is a statistical time chart with 6 clusters. The first cluster is for the title. The second for the two buttons that allow the interactor to change from number of cases to number of dead. The third cluster is the source of data. The fourth cluster is for the 3 drop-down menus to select country, city and period of time. The fifth cluster is the line graph superimposed into the bar graph. The final cluster is the legend. The graph for the number of cases has light blue bars and a dark blue line. The graph for death toll has light gray bars and a black line.
---------------------------------------	---

	Estatísticas Novos casosMortes Fonte: JHU CSSE COVID-19 Data · Última atualização: há 2 dias BrasilSão PauloTodo o período 30.00020.00010.0000 26 de jun.16 de set.9 de dez.1 de mar.22 de mai.12 de ago.2 de nov. 4 de dez. de 2020 Novos casos: 8.237 Méd. de 7 dias: 6.080 Novos casosMédia de 7 dias		cluster 1
			cluster 2
			cluster 3
			cluster 4
			cluster 5
			cluster 6
Source	Google, <https://www.google.com/search?q=covid&source=hp&ei=3uKDYcGDKuHB5OUPy4-qmA&ifsig=ALs-wAMAAAAAYYPw7vzoAWinmurtihAMNlw04wBIEmbl&og=covid&gs_lcp=Cgdn d3Mtd2l6EAMyCAgAEIAEELEDMgsIABCABBCxAXCDATILCAAQgAQQsQMq gwEyCwgAEIAEELEDEIMBMgsIABCABBCxAXCDATIICAAQgAQQsQMMyCwg AEIAEELEDEIMBMgsIABCABBCxAXCDATIFCAAQgAQyCAgAELEDEIMBOg gILhCABBCxAzoLCC4QgAQQsQMqgwE6DgguEIAEELEDEMcbEKMCOhEIL hCABBCxAXCDARDHARCjAjoICC4QsQMqgwE6DgguEIAEELEDEMcbENED QgsILhCABBCxAXCTAjoLCC4QgAQQxwEQowJQtw5YihRqohVoAXAAeACAA YQBIAHjBjIBAZAuNZqBAKABAbABAA&scient=gws-wiz&ved=0ahUKEwjB6onk6v7zAhXhILkGHcuHCpMQ4dUDCAY&uact=5>		
Characteristic that the researcher chooses to highlight	The colors The mode of representation		
SYNTATIC			
Composite syntactic structures			
Simultaneous combination	Background inset		This DV is a shared-axis multi-panel display. It consists of 6 clusters stacked on top of each other, all aligned to the left of the screen. The clusters are: title, buttons for cases/deaths, source, drop-down menus for country/city/days, statistical time chart, and legend.
Nesting	Multi-panel display	Graphic multiple Shared-axis multi-panel	
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation	Size is used to show how many deaths, or cases happened in a determined period of time. The bigger the blue bars are, the more deaths/cases happened. Spatial position is used by the bars to anchor the meaning of the quantity of cases/deaths to a specific day. The position in space that the graphic elements occupy is equivalent to a space in time.
	Area fill attributes	Value Grain Color	Color is used by the cases graph to signify number of cases. The light blue represents the cases in a day, while the dark blue represents the overall average of the pandemic as a whole. Value is used to differentiate between the color for the day-by-day cases (light blue) and the overview of the pandemic (dark blue). For the graph that depicts deaths the same relationship happens, only this time day-by-

			day cases shows up in light gray and the overview is in black.
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition	Separation by separators happens for the bars of the bar graphs. The empty space between them acts as the separation in time between different days. However, this is most easily seen for the graphs for 1 week, 2 weeks and 30 days. For the graph that shows an overall of the entire pandemic, the bars cluster together through spatial clustering and become one single visual element. The bars are organized as a lineup. Linking happens between each point of the line that runs across the bars. The line is also superimposed on top of the bars.
	Object-to-space	Metric space Distorted metric space	The DV makes use of metric space. All elements inside of the graph are anchored to a place and that place has real life meaning. Unlike with a map, the meaning of the position is not anchored to a physical place, but to a place in time.
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier	Labels are used to identify what the horizontal lines mean for the graph, as well as what each of the bars represents. Separators are used both horizontally and vertically. The vertical separators separate between different days, acting as separations in time. The horizontal separators separate concepts, such as number of cases/deaths.
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Grid lines	The bars are surface bars; their position in the space of the surface anchors the concept of death/infection to a time. The line acts as a line locator; it anchors the changes across time as an element that moves across time.
	No anchoring		n/a
SEMANTIC			
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional		There is literal correspondence between the size of the bars compared to the size of the numbers they represent. Their size is proportional and literal when compared to their real life meanings. The metaphor can be found in the color black being used for deaths. It is the metaphor for the absence of light, the night, the concept of death itself, all of which are represented by dark colors. Arbitrary-conventional correspondence can also be applied to the DV. Graphs are well knows visual elements. Interactors are aware that the higher a bar is, the more they signify to that specific date.
Mode of expression	Pictorial Non-pictorial		The bars and line are non-pictorial and use arbitrary conventional correspondences to infer the concept of death and contagion.
Informational roles	Information objects		The bars are one of the most prominent information objects. Their size establishes

			how many cases/deaths happened in a day. Every other day the data is updated and the bars change. The line is another prominent information object, showing to the viewer how the pandemic has been progressing across time.
	Reference objects	Spatial objects	The lines that establish the vertical and horizontal grid. The space between the labels that establishes the change in time.
		Legend objects	There is a legend at the bottom of the DV showing what the colors mean for the representation. There are also labels stating the number of infections on the X and Y-axis. The ones for the X-axis are: 0, 1000, 2000, 3000, 4000, and 5000. The ones for the Y-axis are dates. When the interactor hovers the mouse over a point in the graph a box pops-up and shows the legend specific for that day. It consists of the information about the date, number of new cases and average of 7 days.
	Decoration objects		n/a
Interactions	Zoom Search and locate Filter Details on demand History Extract Link and brush Projection 8.3.1 Distortion		The DV allows for the function of filtering. The interactor can filter by country, state, number of days, etc. It also provides details on demand when the interactor hovers the mouse over specific spots in the DV. This triggers a little box to appear and show some more information on that specific day (figure 55).
CLASSIFICATION OF GRAPHIC REPRESENTATIONS			
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network		
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram		Statistical time chart. It combines the statistics of charts with the passage of time. Each space on the grid is anchored to a different moment in time.
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons		This DV's main focus is on trends (process and time). It serves so the interactors can see how things have changed across time and make predictions about the future. It

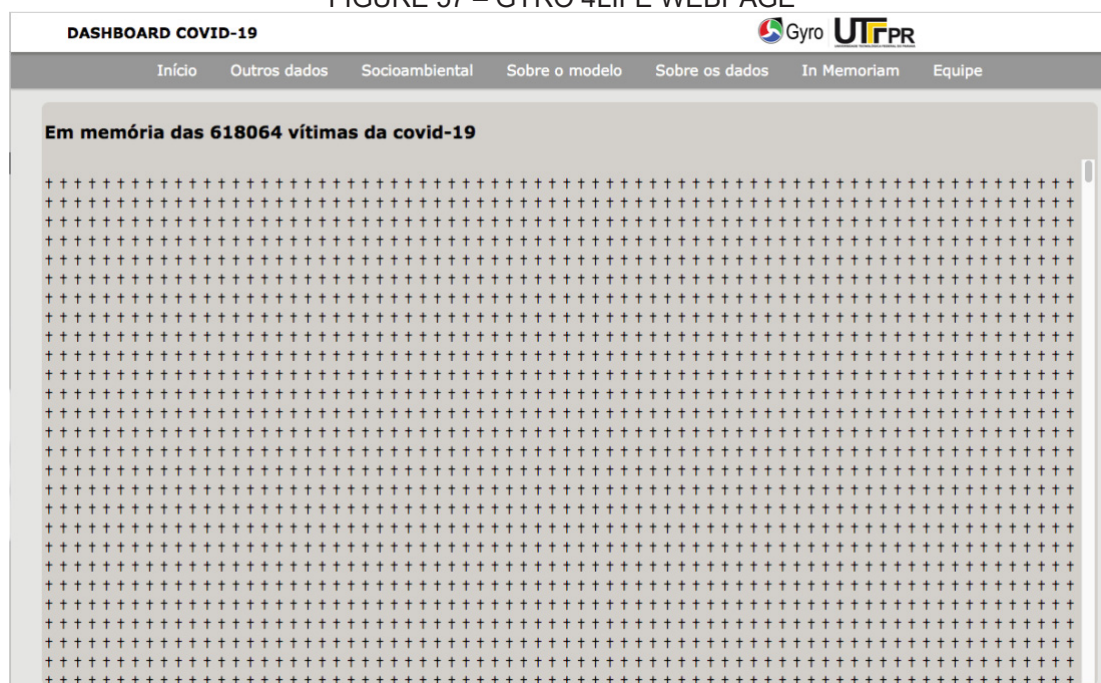
	Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	also allows for distribution and finding outliers – i.e. when there is a sudden spike in cases out of seemingly nowhere. Another insight that the interactors can glean from the DV is about comparisons. This would require the interactor switch between different countries/cities so they can compare how the pandemic is happening there in comparison to other places.
Data scales	Nominal Ordinal Interval Ratio	The data represented in the DV is ratio. It has a real zero – i.e., no cases or no deaths, and the interval between data points is tangible.
Analysis	Statistical Temporal Geospatial Topical Relational	The analysis for this DV is mainly temporal as it seeks to compare the pandemic data from one day to another and make predictions about the future.
ELEMENTS OF ENGAGEMENT		
Storytelling	Narrator	n/a
	Tellability	Tellability can only be fully known once interactor testing happens. However, some design elements can come to foster this feeling in the interactor. There is certain tellability to this DV as it concerns a pandemic that is very relevant globally. However, few elements emphasize meaning precisely because the DV presents the content with minimal emotion.
	Sequentially	The sequentiality of this DV comes from its representation of time. Each bar represents a day and is followed by the next one, creating a time line of the pandemic. Furthermore, the line that moves over the bars creates a connection between one point in time to the next mimicking a narrative that runs through different points in time.
	Temporal dimension	Temporal dimension follows the same parameters of sequentiality. The DV presents time as space. Different spaces in the DV represent different times. The DV spans across 1 week to the beginning of the pandemic.
Perspective shifting		There is no perspective changing. The interactor can change the span of time the DV represents, but the content and style of information remain unchanged.

SOURCE: the author

8.4 GYRO

The last DV analyzed was by GYRO UTFPR, a laboratory connected to the Federal Technological University of Paraná. The website where the DV is located has a dark gray menu separated into “home”, “other data”, “socio-ecological”, “about the model”, “about the data”, “In Memoriam”, and “team” (in Portuguese: “início”, “outros dados”, “socioambiental”, “sobre o modelo”, “sobre os dados”, “In Memoriam”, and “equipe”). The DV is on a website page called “In Memoriam” (figure 57).

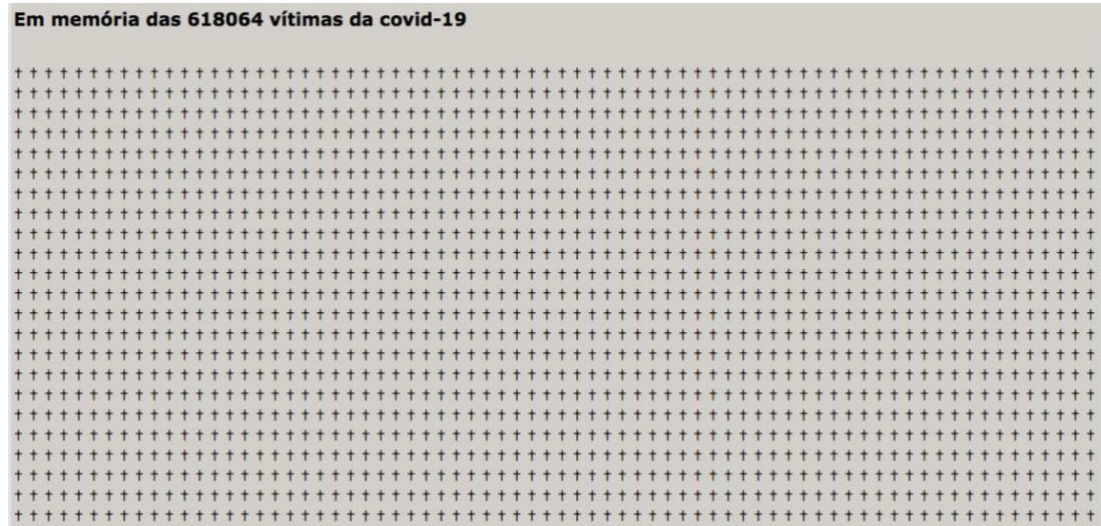
FIGURE 57 – GYRO 4LIFE WEBPAGE



SOURCE: GYRO 4life. Available on:
https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NqvW-FgrnHmVvVrFCitiANyYSmlWBXEO_m6-M857sOgykg#. Accessed: 20 December. 2021.

On the top left corner, there is the bolded title of the DV, called “In memory of the 618064 victims of covid-19” (*“Em memória das 618064 vítimas da covid-19”*). Right below the title begins the wall of crosses. There are 72 columns, and the rows get updated as the number of deaths grows. There is a scroll bar to the right of the visualization (figure 58).

FIGURE 58 – GYRO 4LIFE DATA VISUALIZATION



SOURCE: GYRO 4life. Available on:

<https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NqvW-FgrnHmVVrFCitiANyYSmlWBXEO_m6-M857sOgykg#>. Accessed: 20 December. 2021.

The crosses are simple, made out of two straight lines that intersect (figure 59). The only interaction available to the interactor is scrolling down the page to see the wall of crosses. The analysis of this DV follows below on CHART 14.

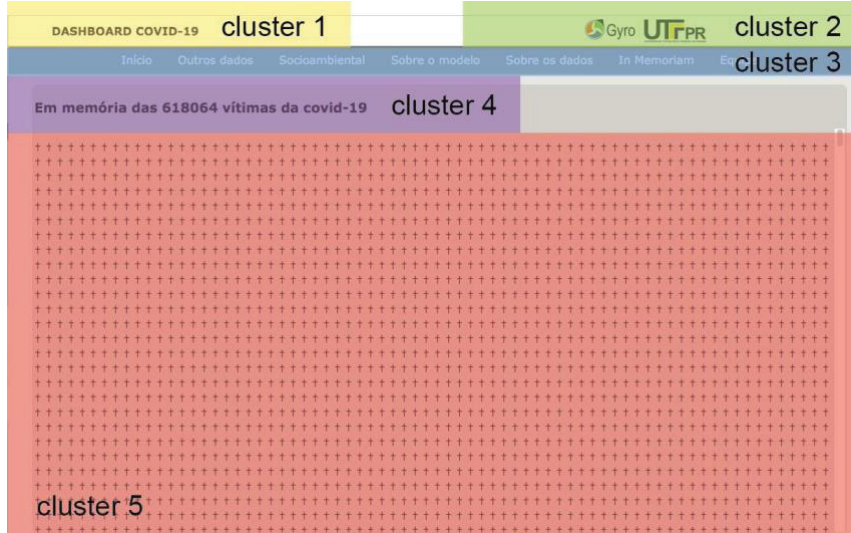
FIGURE 59 – GYRO DV, DESIGN OF THE CROSSES



SOURCE: GYRO 4life. Available on:

<https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NqvW-FgrnHmVVrFCitiANyYSmlWBXEO_m6-M857sOgykg#>. Accessed: 20 December. 2021.

CHART 14 – ANALYSIS OF THE GYRO DV

Description of the data visualization	The website where the DV is has 5 clusters. The first cluster introduces the purpose of the page, which is to be a dashboard to keep track of COVID-19 deaths. The second cluster has the logos for the laboratory and the university. The third cluster is the menu for the webpage. The fourth and fifth clusters are the ones that comprise the DV. The fourth cluster introduces the title of the DV. The fifth cluster is the cluster of black crosses that occupies the entire screen of the webpage. 		
Source	GYRO website < https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NqvW-FgrnHmVVrFCitiANyYSmIWBXEO_m6-M857sOgykg# >		
Characteristic that the researcher chooses to highlight	The crosses The clustering of the crosses The storytelling The interaction as scrolling		
SYNTATIC			
Composite syntactic structures			
Simultaneous combination Nesting	Background inset		There is no nesting in the DV. Every element is located side by side on a beige background.
	Multi-panel display	Graphic multiple Shared-axis multi-panel	
Visual attributes (given to graphic objects)	Spatial attributes	Shape Size Spatial position Orientation	Crosses are used as the shape to represent the gravestones. Their spatial position is in a grid of 72 columns with rows that get added when the data it updated. Size is applicable to the cluster of crosses, the bigger and longer it gets, the more people have died.
	Area fill attributes	Value Grain Color	
Syntactic structures (relationships between graphic objects)	Object-to-object	Spatial clustering Separation by separators Lineup Linking Containment Superimposition	Spatial clustering happens to the crosses. When they are gathered through the grid they are placed on, they become a single entity that the interactor can scroll through. The crosses are lined up in columns of 72 each, with rows that grow the more deaths occurs. The crosses are contained inside of the beige box that limits the space of the DV.

	Object-to-space	Metric space Distorted metric space	The DV uses metric space to position the crosses in different places of the screen. Because of the positioning of the crosses, the DV gives the idea of being a cemetery, thus making the metric space in the DV correlate to the space in a cemetery,
Syntactic roles of graphic objects	Object-to-object anchoring	Node Label Separator Connector Container Modifier	n/a
	Object-to-space anchoring	Point locator Line locator Surface locator Volume locator Metric bars Grid lines	The crosses create grid lines because of the way they are organized in neat columns and rows. They also act as point locators, anchoring the idea of a human death to a space in the metaphorical cemetery that is the representation.
	No anchoring		n/a
SEMANTIC			
Type of correspondence	Literal Metaphoric Metonym Rebus-based Arbitrary-conventional		The crosses use several types of correspondence. First, they are literal representations of tombstones, as many graves use crosses on top of the where the body is buried. Secondly, they use metaphoric correspondence between the cross and the concept of death. They are also considered to be a conventional symbol to represent graves, thus also falling under arbitrary-conventional correspondence.
Mode of expression	Pictorial Non-pictorial		The crosses are pictorial modes of representation.
Informational roles	Information objects		The crosses act as the main information object. Each one represents another person lost to COVID. The title is also an informational object as it shows the interactor the exact number of the deceased, since the crosses do not provide the exact number by themselves. The crosses serve to inform the interactor about the feel and scope of death, while the title informs them about the precise number of those that were lost.
	Reference objects	Spatial objects	The invisible grid that the crosses are on establishes the spatial arrangement of the DV.
		Legend objects	The legend of the DV is the title itself. It explains briefly what the DV is about and gives context to the deaths.
	Decoration objects		n/a
Interactions	Zoom Search and locate Filter Details on demand History		None of these interactions are applicable to this DV.

	Extract Link and brush Projection Distortion	
CLASSIFICATION OF GRAPHIC REPRESENTATIONS		
Primaries	Map Picture Statistical chart Time chart Link diagram Grouping diagram Table Symbol Written text Graph Tree Network	Picture. This DV shows an image that functions in much the same way a picture of a cemetery would. The focus is on the shock it can cause on the interactor and the power it has to represent the tragedy that was the pandemic. It is not trying to explain data, just to present the story behind it.
Hybrids	Statistical map Path map Statistical path map Statistical time chart Statistical link diagram Chronological link diagram	
Insight needs	Categorize/cluster Order, rank, sort Distribution (also outliers) Comparisons Trends (process and time) Geospatial Compositions (also of text) Correlations/relationships	None of these fit the DV.
Data scales	Nominal Ordinal Interval Ratio	The DV uses a ratio data scale.
Analysis	Statistical Temporal Geospatial Topical Relational	n/a
ELEMENTS OF ENGAGEMENT		
Storytelling	Narrator	The narrator of this story appears as the interactor scrolls through the webpage and sees all of the graves. Scroll telling is used as a way to insert the viewer in the story of walking through a cemetery and soaking in the death.
	Tellability	The tellability of this DV comes from the theme, since COVID is a global event.
	Sequentiality	There is no sequentiality in the DV. The representation presents only the present. The interactor has no way of knowing how many deaths there were tomorrow because the DV does not separate by time. The interactor could get an idea of a

		sequence if they came to the website on different days and compared the numbers from one day to another, but the DV does not provide the sequence by itself.
	Temporal dimension	Temporal dimension can be perceived by the interactor if they open the website on different days and compare what changed in the data. Otherwise, the DV only presents the present as it is.
Perspective shifting		There is no perspective changing.

SOURCE: the author

9 DISCUSSION

This chapter discusses how data visualization has been using graphic elements to represent data about death and contagion and its possible connections to the way people perceive their mortality and agency. The discussion in this chapter fulfills the third specific objective of this dissertation.

The discussion was separated into three parts. Each one discusses one of the DVs, starting with JHU, Google, and GYRO. The discussion is organized following the analysis: syntactic, semantic, classification of graphic representation, and engagement elements.

The discussion sections get progressively smaller because of the complexity of the data visualizations. John Hopkins University is the most complex data visualization, with a large number of elements and pages, while Google and GYRO are both single pages with minimal interaction. Because of this, the analysis for JHU spans much longer than the other two.

9.1 JOHN HOPKINS UNIVERSITY

9.1.1 Syntactic

The most significant visual elements for this DV are the circles. Their color and size act as a metaphor for contamination and the number of cases. Red represents the infected. The more a country is colored, the more it is contaminated. The colors act as both a metonym and a metaphor, invoking the idea of contagion, blood, danger (VON ENGELHARDT, 2002).

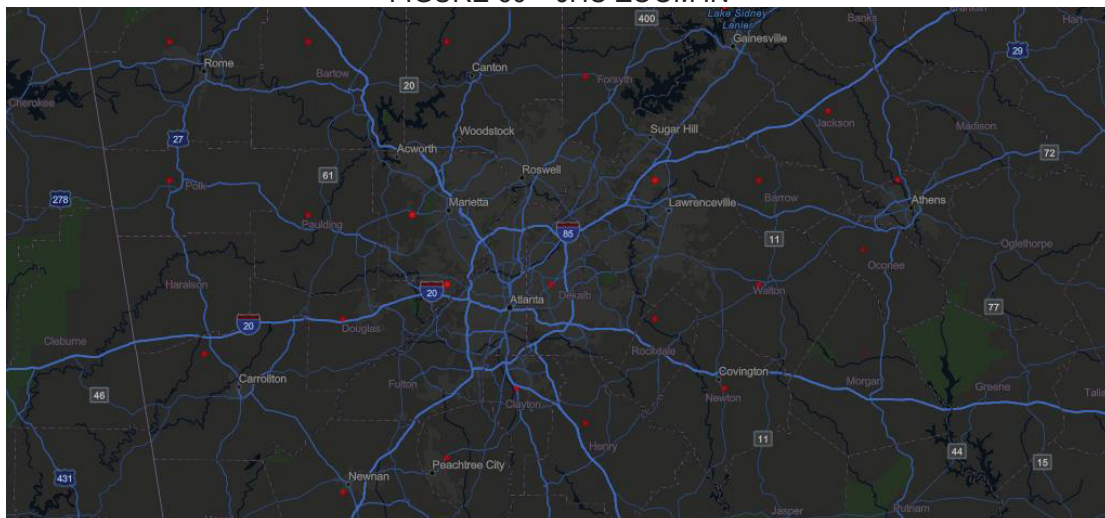
Additionally, the size represents the growth of the pandemic, and the larger the circle, the bigger the danger. The map intends to make interactors compare the pandemic situation between countries or continents. When the map is at the global scale (figure 41), the circles cluster together, and the interactors might stop seeing them as individual data points and instead begin seeing them as one mass (VON ENGELHARDT, 2002). The circles press into one block of information and are processed as a singular unit.

This visualization might trigger death anxiety and feed the message of “us against them” because the infection levels of a country cluster together

into a single representation, the interactors can compare the state of their country to other countries. This unity might foster the idea that the other can posit a danger – i.e., infecting their country –, or harbor the understanding that the world is one and all people should be cared for (GREENBERG; ARNDT, 2012).

Additionally, the map loses information when the interactors zoom in. When zooming in, the circles do not maintain their size compared to their surroundings but shrink. A country that seems riddled with an infection on a global view turns into a country that barely has any cases when zoomed in. Figure 60 shows this form of scaling, where the city of Atlanta seems to have close to no cases. The circles are so small that they can barely be seen through the blue lines representing the roads.

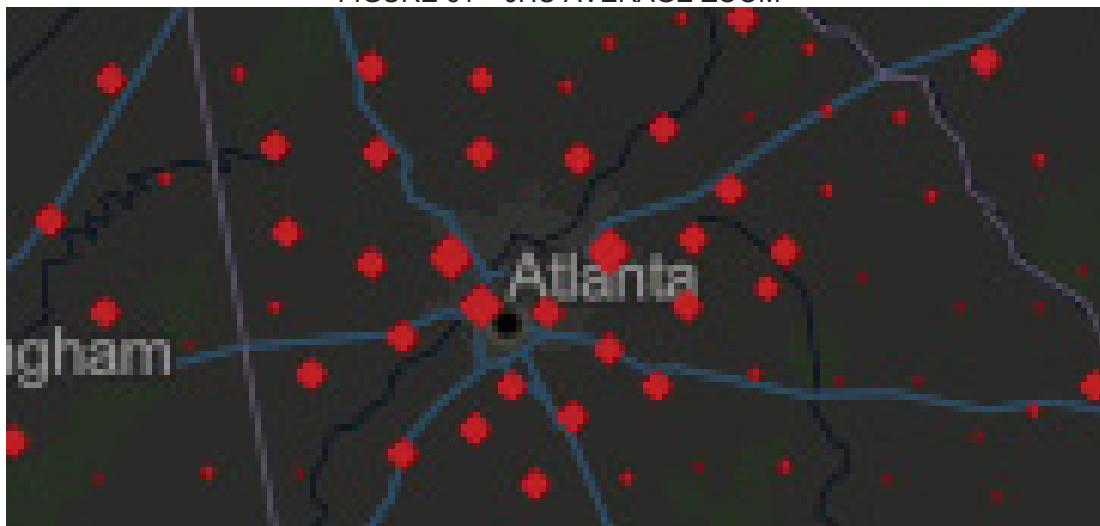
FIGURE 60 – JHU ZOOM IN



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

Comparing the zoomed-in image with a less zoomed-in view of Atlanta (figure 61) reveals that the circles – or diamonds because of the screen definition – grow as the interactor zooms out. Figure 61 shows an Atlanta that seems to have more cases than the Atlanta in figure 60, even though nothing in the data changed between the two.

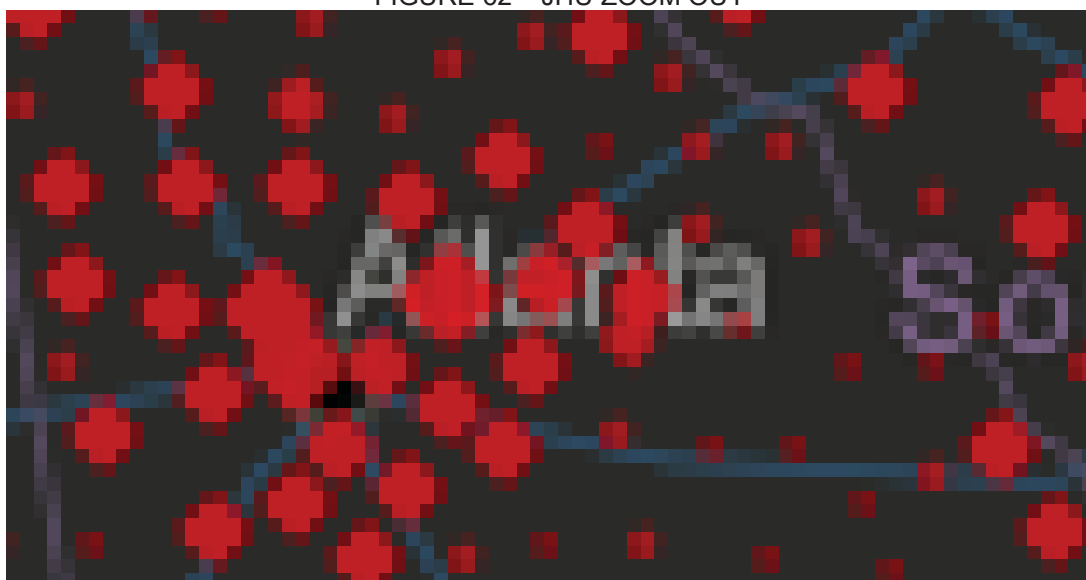
FIGURE 61 – JHU AVERAGE ZOOM



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

Zooming in further, figure 62 shows Atlanta, with the circles occupying so much space that the blue lines representing the roads or the city's name can barely be seen. According to this visualization, this is the most dangerous Atlanta of them all, despite all three simultaneously being the same place. Danger is represented by the size and color of the circles, forming an infection structure (VON ENGELHARDT, 2002).

FIGURE 62 – JHU ZOOM OUT



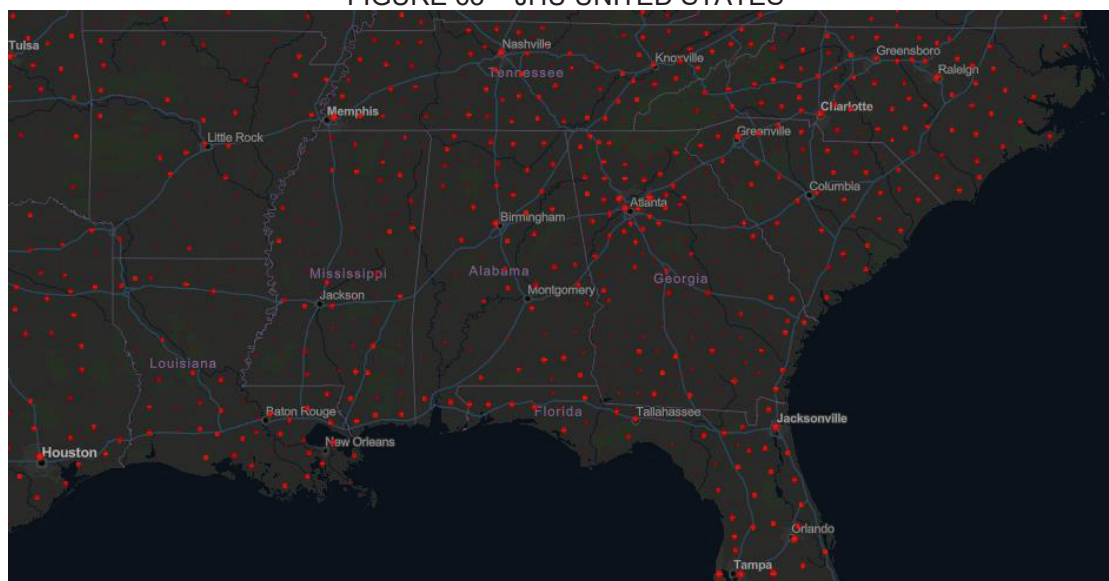
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

Additionally, the visualization does not present the same level of data complexity for all countries. The information for the United States is much more detailed than for the other countries, despite the claim that it is a global dashboard. Figures 63 and 64 show both the United States and Brazil at the same zoom level.

The USA has far more red circles in different locations, although they are smaller than the ones located in Brazil. Because of this representation, the USA seems much more dangerous than Brazil, with a far more spread-out disease, albeit with less clustering of contagion.

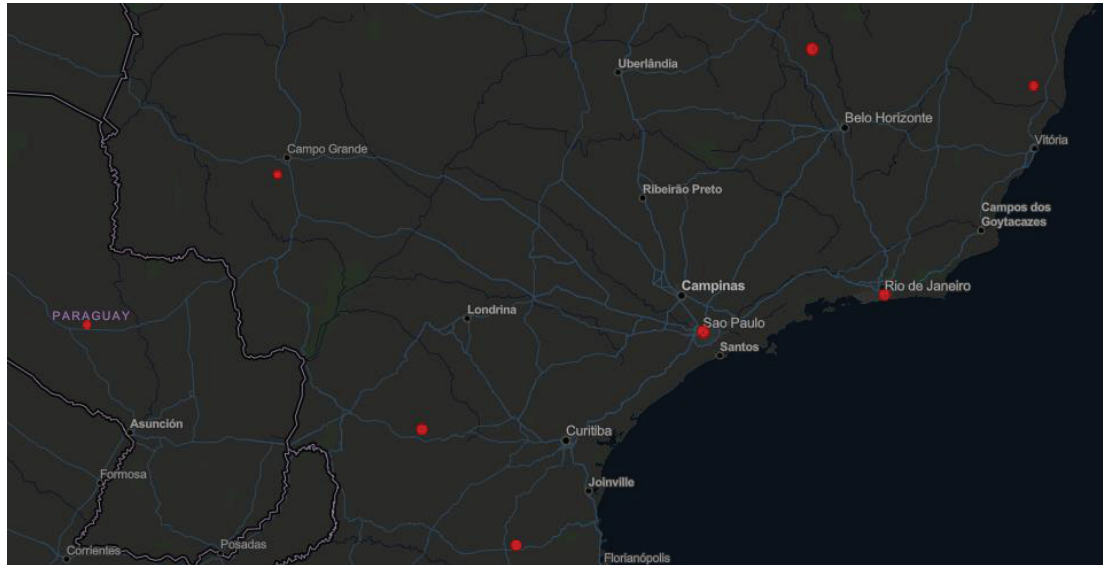
On the other hand, for Brazil, the DV communicates that there are very few cities with any cases, but the ones that do have high numbers of contagion. For example, the data visualizations show that there are no cases for Curitiba, which is false (CORONAVIRUS CURITIBA, 2022).

FIGURE 63 – JHU UNITED STATES



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

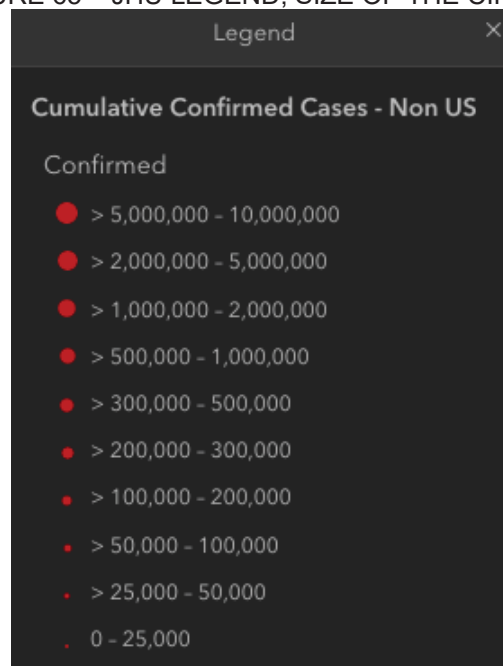
FIGURE 64 – JHU BRAZIL



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

The size of the circles might also come to confuse the interactor, as they do not have enough distinguishable visual differences (VON ENGELHARDT, 2002). Figure 65 shows the legend of the DV. The difference in size between the circles is so tiny that it may be hard for the interactor to distinguish between the circle that represents 5,000,000 to 10,000,000 and the one that represents between 2,000,000 to 5,000,000.

FIGURE 65 – JHU LEGEND, SIZE OF THE CIRCLES

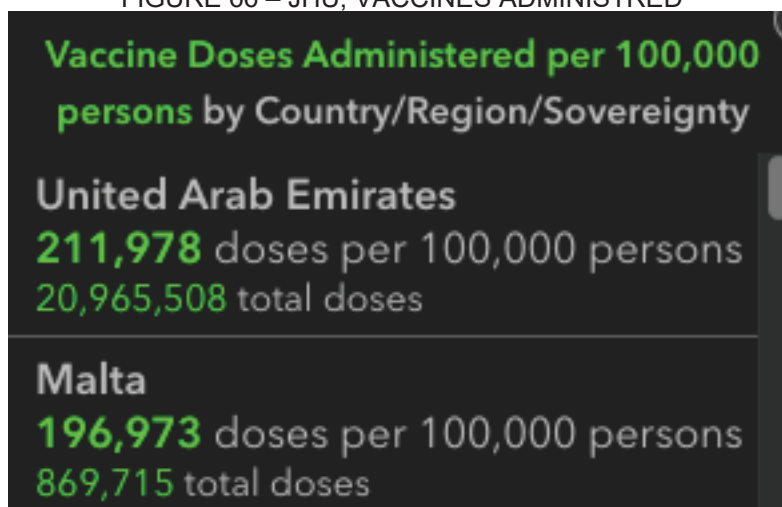


SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

Another element that might confuse the interactor is the interpretation of the section of the DV that presents data on vaccine rates. Figure 66 shows the legend for the number of vaccines administered per 100,000 persons. However, the numbers showcased say that there have been 211,978 doses per 100,000 persons. The numbers may require some interpretation and do not differentiate between the vaccines that need two doses and those that need a single amount.

Presenting the information using numbers and the text invites the interactor to stop and interpret what the text in the DV is trying to say, so it might add confusion, and any element that confuses the interactor and makes them unsure of what they see affects agency. If the interactor does not feel confident in the information, they cannot act upon it (EICHNER, 2014; VON ENGELHARDT, 2002).

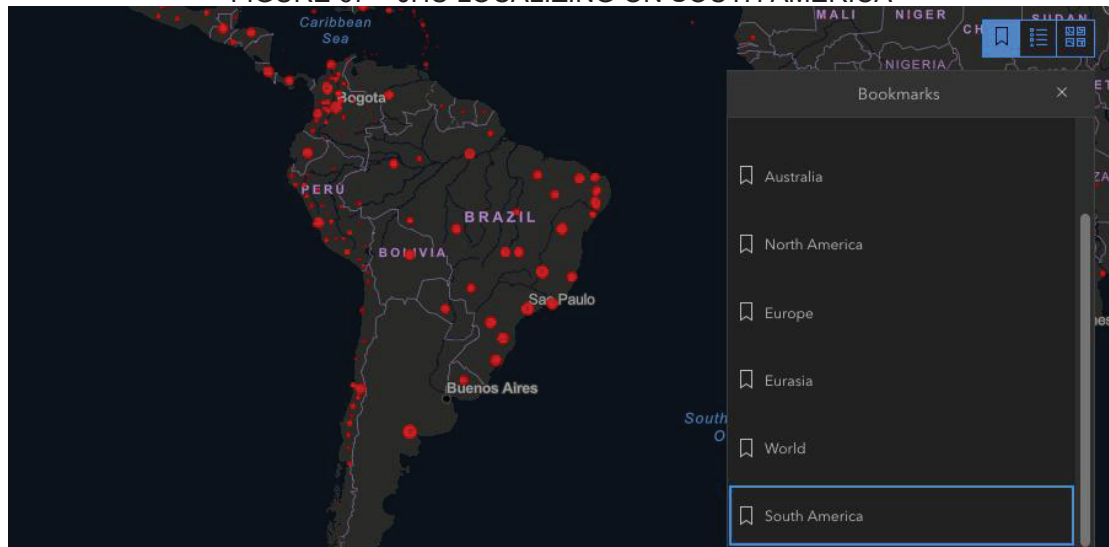
FIGURE 66 – JHU, VACCINES ADMINISTRED



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

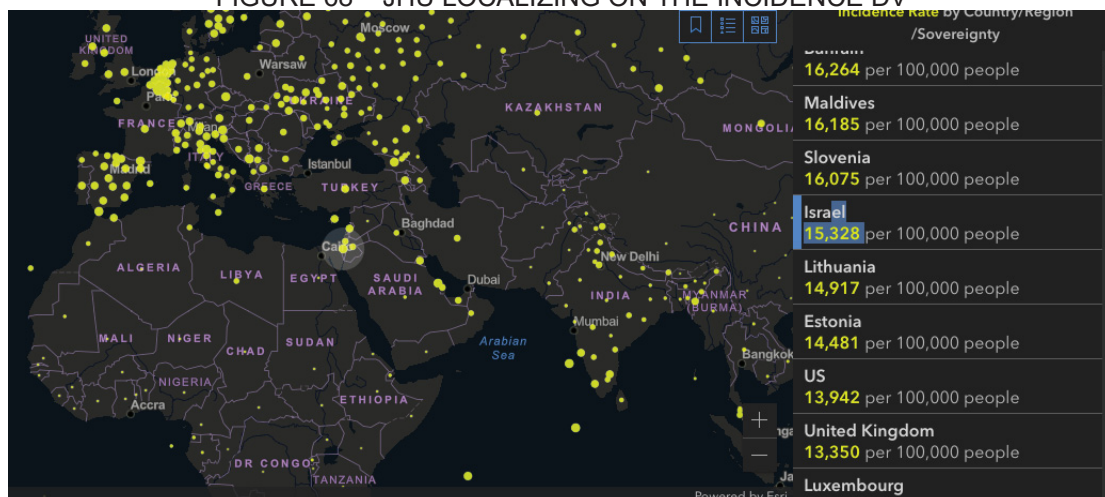
Spatial positioning plays a significant role in this DV. The map has two features for localizing the interactor in the map. The first one is the bookmark tab (figure 67), which moves the camera to the country of choice when clicked on. This bookmark is not static, and if the interactor zooms in/out or moves the mouse, the country leaves the focus. The second locating feature is for the Incidence DV. When the interactor clicks on the country, a small white circle blinks on top of the country, locating the chosen place (figure 68).

FIGURE 67 – JHU LOCALIZING ON SOUTH AMERICA



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 30 Oct. 2021.

FIGURE 68 – JHU LOCALIZING ON THE INCIDENCE DV



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 30 Oct. 2021.

9.1.2 Semantic

Because the DV is a map, there is meaning to the position of the colored dots. They are explicitly anchoring a concept to a geographical place (VON ENGELHARDT, 2002). Red dots carry the idea of contagion, white dots of death, yellow dots of incidence cases, and green of vaccine rates.

Localizing either the interactor or the concept of contagion to the map might incite feelings of fear once they localize themselves on the map and see that

the red surrounding their location means danger (GREENBERG; ARNDT, 2012; ROSENBLATT et al., 1989; VON ENGELHARDT, 2002).

Locating the interactor on the map can come to foster both death anxiety and death reflection. When finding an interactor on the map, the DV might foster the feeling of “us against them” once the interactor sees they belong to a geographical location and believes that the others are their enemies. This could align with the self-protective nature of TMT and TMHM (GREENBERG; ARNDT, 2012; ROSENBLATT et al., 1989). However, it might also foster empathy as the interactor compares their situation with others around the world and shifts to a more global approach and pro-social behavior (LYKINS et al., 2007).

Color, shape, and size are the essential informational elements of the DV. They are the ones that convey the data to the interactor by changing size, color, and location. However, they also have characteristics that could come to evoke death anxiety. The red of the dots and the way they seem to spread like infecting tissue are all elements that might incite the interactor's fear and emotional responses (GREENBERG; ARNDT, 2012; PYSZCZYNSKI et al., 2020; ROSENBLATT et al., 1989; VON ENGELHARDT, 2002).

On elements that could cause relief for the interactor might be zooming out and seeing fewer deaths in your country/city/town than the rest of the world. Comfort might come from placing oneself on the map through self-localization and understanding what those white dots mean to you, what they represent, and that they anchor the concept of death to your geographical location (EICHNER, 2014; GREENBERG; ARNDT, 2012; MURRAY, 1997; VON ENGELHARDT, 2002).

This DV shows large quantities of information to the interactor and focuses on the global toll this pandemic caused humanity. Because of the scale of the representation, the interactor might lose sight of the importance of individual actions and become overwhelmed with the state of the world. If this happens, then the DV might cause less empathetic responses and less engagement (COOLEY, 2020).

Furthermore, the mode of representation is more schematic, which risks reducing the scale of human life loss to numbers, which also might

contribute to the loss of empathetic responses (COOLEY, 2020; HEPWORTH, 2016).

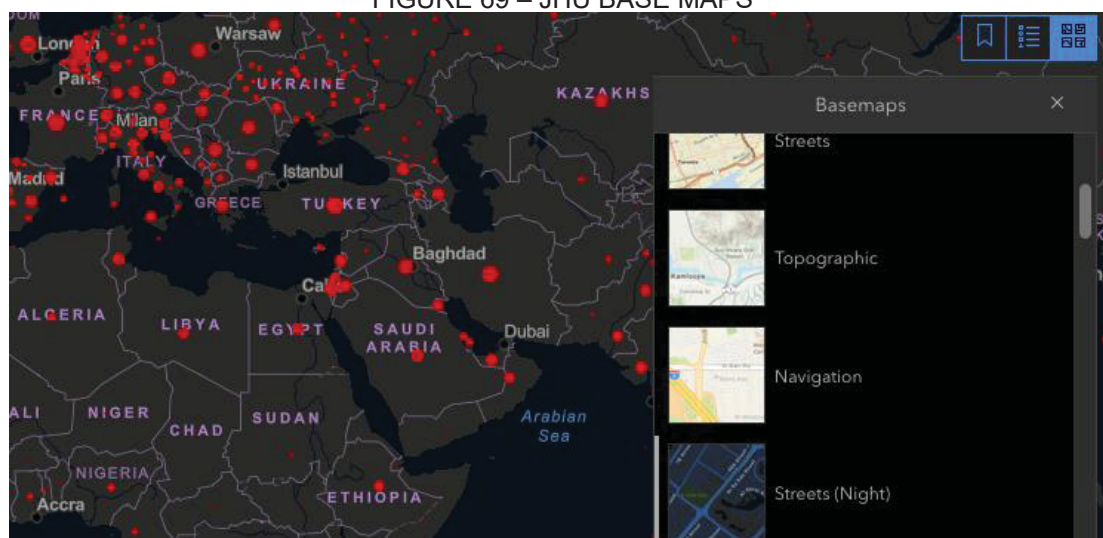
9.1.3 Classification of graphic representations

This data visualization is a statistical map, which combines the elements of statistical charts with geographical location (VON ENGELHARDT, 2002). The DV works very well as a global overview of the state of the world. When the interactor first opens the webpage, the map is set to a very zoomed-out view.

Several elements from Google Maps are incorporated in the DV, such as the primary interface and the option to change the style of the map. Using the button in the upper right corner, the interactor can change what the map looks like (figure 69).

The original map is the 'Streets (Night)'; however, there is no indication. If the interactor clicks on another map, there are no indicators to guide them back to the original. The original map is in the middle of the scroll-down menu, and it might be hard for the interactor to find it again.

FIGURE 69 – JHU BASE MAPS

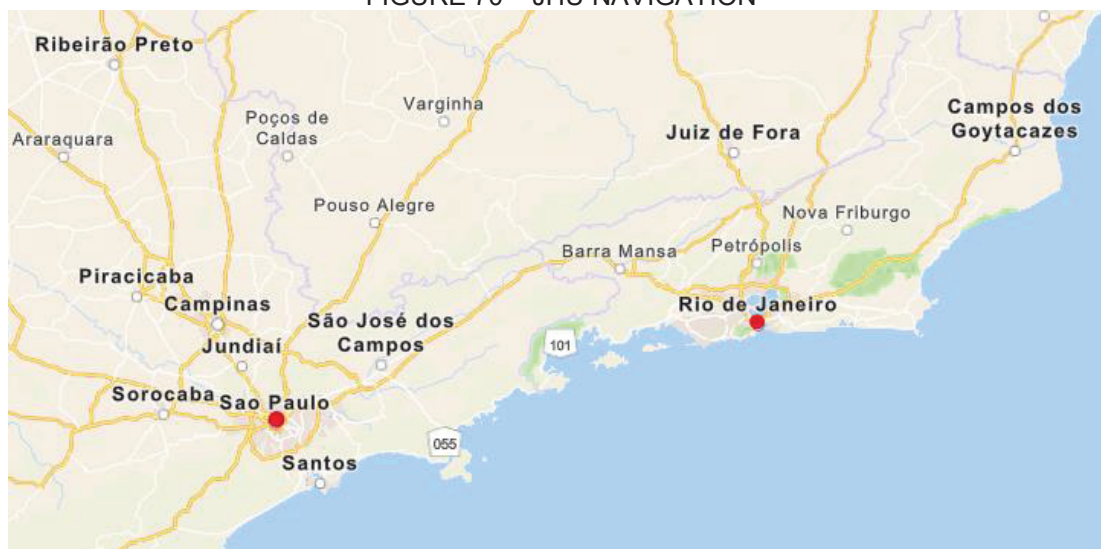


SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

There are various base maps, some that seem to come from Google Maps (figure 70), and others that lean more towards artistic (figure 71). These

other maps serve no apparent purpose. Furthermore, some of them seem to distract from the informational purpose of the DV – i.e., the imagery map that is so full of texture, details, and colors it might be hard even to see the red dots (figure 72). All of these seem to be stylistic choices that could potentially go against the informational purpose of the DV (MAYER, 2003; VON ENGELHARDT, 2002).

FIGURE 70 – JHU NAVIGATION



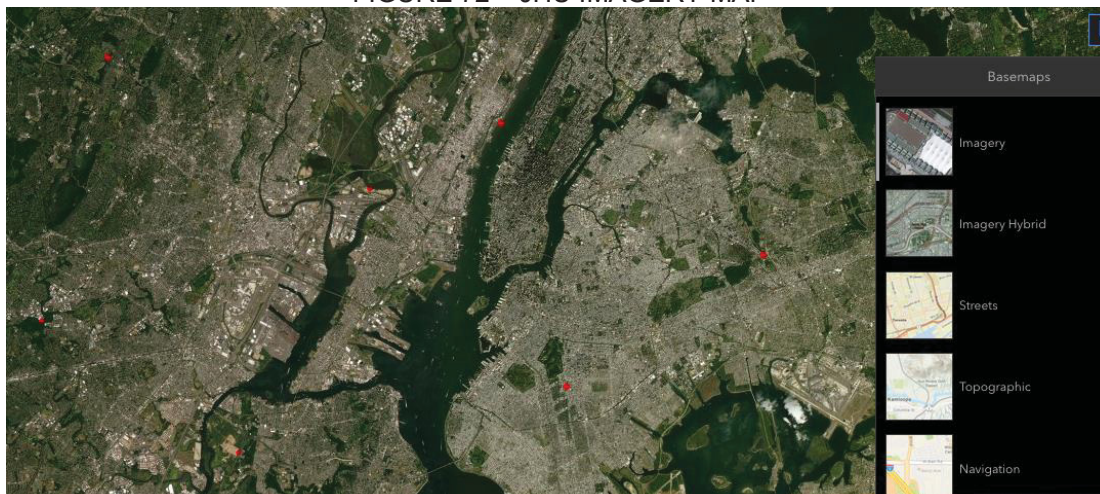
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

FIGURE 71 – JHU MID-CENTURY MAP



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 26 Oct. 2021.

FIGURE 72 – JHU IMAGERY MAP

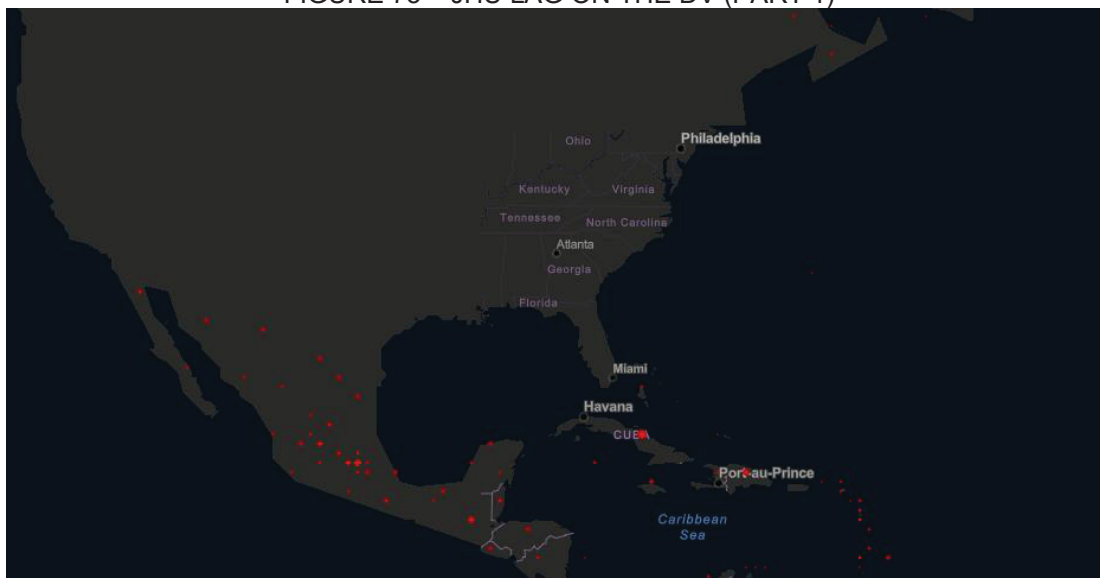


SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 2 Nov. 2021.

9.1.4 Elements of engagement

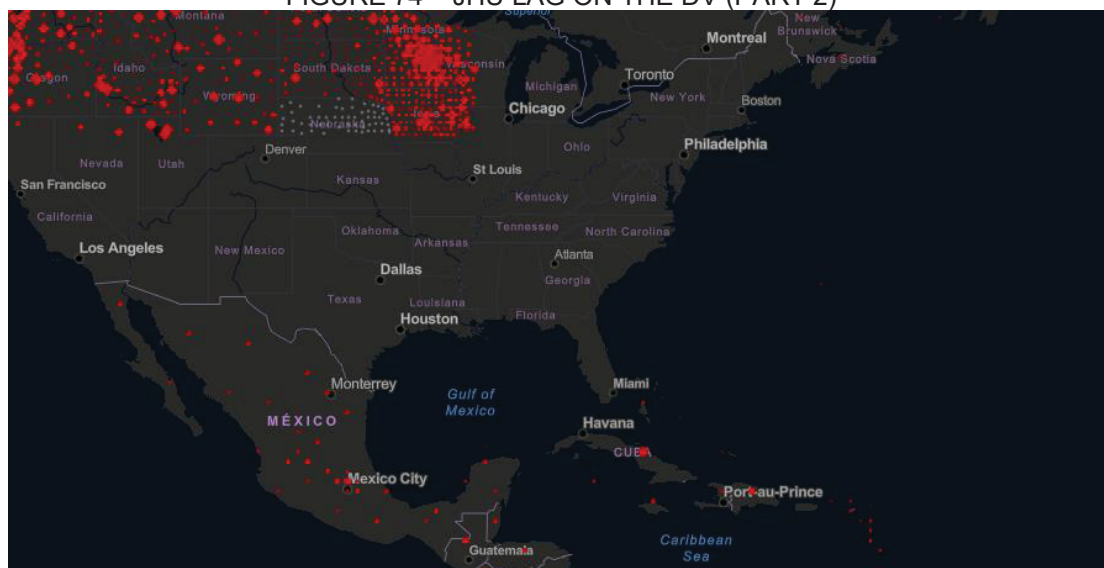
The most apparent mode of interaction with the DV is click-and-drag and zoom in/out, both of which happen with much lag. The map sometimes takes up to 15 seconds to load the images, leaving the interactor with blank spaces (figures 73–76).

FIGURE 73 – JHU LAG ON THE DV (PART 1)



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 02 Nov. 2021.

FIGURE 74 – JHU LAG ON THE DV (PART 2)



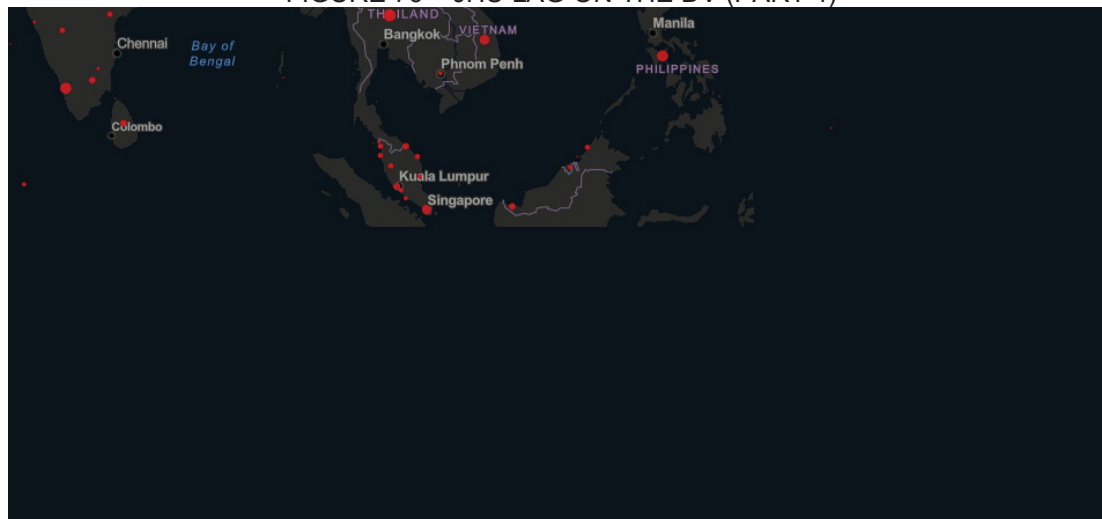
SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 02 Nov. 2021.

FIGURE 75 – JHU LAG ON THE DV (PART 3)



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 02 Nov. 2021.

FIGURE 76 – JHU LAG ON THE DV (PART 4)



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 02 Nov. 2021.

The zoom can be controlled using the buttons labeled “+” and “-” on the lower right corner of the screen, using the mouse’s scroll wheel, or a trackpad. All of them present the same lag and prolonged loading. Additionally, the calibrations of the trackpad and scroll wheel are off and it is easy to scroll down too much or too little when using them. The DV’s control over the zoom in/out features is slow and clunky.

These elements can potentially significantly impact interactor’s agency (EICHNER, 2014; MURRAY, 1997). When the interactor cannot master control over the controllers of the DV, the agency that could happen via either mastering space, or action might be traded for frustration (MURRAY, 1997).

In conclusion, the informational design elements in the DV are mediocre. There are many elements that might come to confuse the interactors and a lack of adaptability of the DV for different types of zoom. The DV seems to work best with less zoom, which is what the website suggests by leaving the option with least zoom as the standard version an interactor would see upon opening the webpage (figure 77). This view allows the interactor to compare continents and experience the difference in the spread of the pandemic. The circles cluster together, and the interactor does not need to spend the cognitive effort to figure out what the different sizes mean because the difference becomes instinctive.

FIGURE 77 – JHU INITIAL VIEW



SOURCE: John Hopkins Coronavirus Research Center. COVID-19 Dashboard. Available on: <https://coronavirus.jhu.edu/map.html>. Accessed: 02 Nov. 2021.

CHART 15 has a summary of the most striking elements of this visualization, alongside the way in which they could come to incite death awareness.

CHART 15 – RELATION BETWEEN VISUAL ELEMENTS AND DEATH AWARENESS, JHU

Visual elements	Death awareness	How it happens
Red circles	Anxiety	Syntactic • Visual attributes: shape and color • Syntactic structures: clustering • Syntactic role: point locator Semantic • Correspondence: Metaphor, metonymy arbitrary convention • Informational role: informational object
Map	Anxiety	Semantic • Correspondence: literal • Elements of engagement: <i>Tellability</i>
	Reflection	Semantic • Correspondence: literal • Elements of engagement: <i>Tellability</i>
The pictorial nature of the representation	Reflection	Semantic • Pictorial mode of representation
Interaction through clicking	Reflection	Element of engagement • Narrative

SOURCE: the author

9.2 GOOGLE

9.2.1 Syntactic

The element that this DV seems to place the most focus on is the number of new cases. This is the information represented as default, which automatically sets to the country the interactor is located in.

The colors used for the new cases are two different tones of blue. This is the opposite of what was done at JHU, which used reds and black. On the other hand, Google opts for white and blue, colors that might incite less fear and guttural responses. The color blue could come to steer interactors into logical responses, as it activates “cool” cognitive processing and favors death reflection over death anxiety (GRANT; WADE-BENZONI, 2009; GREENBERG; ARNDT, 2012; METCALFE; MISCHEL, 1999; VON ENGELHARDT, 2002).

Size is used to measure the infection rates of a particular time. The bigger the bar, the more people were infected. Similar to the JHU visualization, there is a direct correlation between size and danger (VON ENGELHARDT, 2002).

When the DV is focused on the entire pandemic, the bars that mark the infections for each day are clustered together to the point of being seen as a single unity (figure 78). However, the bars become separate elements when the DV shows info about a limited period (figure 79).

FIGURE 78 – GOOGLE DV, BARS AS A SINGLE UNIT

Estatísticas



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

FIGURE 79 – GOOGLE DV, BARS AS SEPARATE UNITS



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 04 Nov. 2021.

9.2.2 Semantic

There is a parallel between the size of the bars and the number of deaths. Also, the concept of death is anchored to a specific time. Each bar represents a different number of cases or casualties that happened in a day. It

is easy for the interactor to see the bars as a unit when they connect through grouping (VON ENGELHARDT, 2002). This, coupled with the line across the bars, gives the DV a narrative that flows through time (WEBER, 2020).

Additionally, this format of visual representation is a standard when trying to show changes across time. The way it is designed borrows many elements from time charts that came before. The DV has no aspects that evoke the thought of death or contamination; instead, it presents itself as neutral and generic as possible. The only indicator that this DV deals with serious content is the tab that mentions death and the rest of the web page's general context. If taken in isolation, the DV could be about a lot of things.

To illustrate, FIGURE 80 shows the data visualization that Google uses to represent the stock situation. The way the data is represented is the same, even though one of them deals with the real loss of human life and the second with the economy. Almost identical representations for subjects that are very different in actual content.



SOURCE: Google. Stocks Search Page. Available on: Google. Accessed: 09 May. 2022.

The DV seems to have been designed focusing on the technology behind it rather than the design. It is a chart that might be easy to update and requires little data transformation to make something that the average viewer can consume. Because of this, the content of the data – i.e., death – might have a chance of getting lost in translation (HEPWORTH, 2016).

9.2.3 Classification of graphic representations

The DV is a statistical time chart and thus, places most of the focus on the changes that happen during a period. This kind of DV is often used to predict the future (see Chen et al., 2020; Wu; Badshah; Bhagwat, 2019) so the interactors can project what they believe will happen based on what the DV shows.

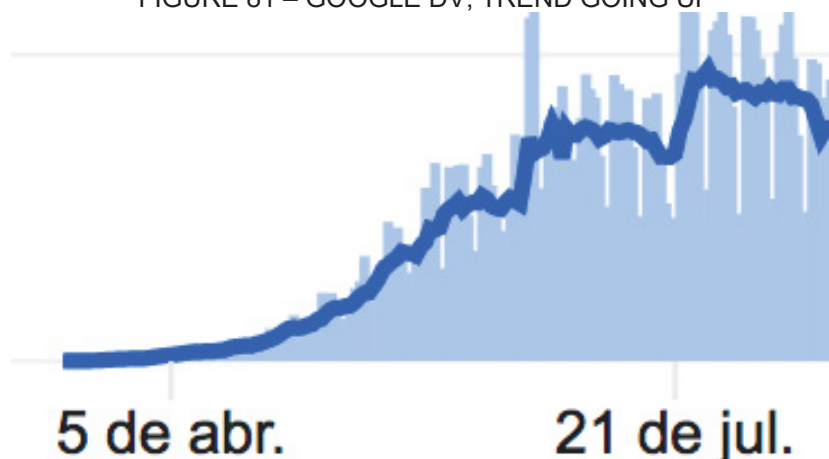
9.2.4 Elements of engagement

The most significant role is to display the number of new cases, or deaths, in a period. Because of this, the DV has graphical elements that might foster sequentiality and temporal dimension, therefore borrowing storytelling elements (WEBER, 2020).

There seems to be little emotion behind the narrative, as most information is presented as neutrally as possible, but the ebb and flow of the cases growing and lowering may incite the interactor to perceive a narrative (COOLEY, 2020; HEPWORTH, 2016; WEBER, 2020). The way the DV is structured, sudden spikes and lows might cause fear or euphoria to the interactor (GREENBERG; ARNDT, 2012; WEBER, 2020).

The interactor can see the progression of the pandemic in the past and, based on it, might make predictions. If the line starts to go up again, it is reasonable to expect that the situation will deteriorate and a new wave will come (i.e., figure 81). If the line starts tipping down, the interactor might infer that the worst has passed (i.e., figure 82).

FIGURE 81 – GOOGLE DV, TREND GOING UP



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 08 Jan. 2022.

FIGURE 82 – GOOGLE DV, TREND GOING DOWN



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 08 Jan. 2022.

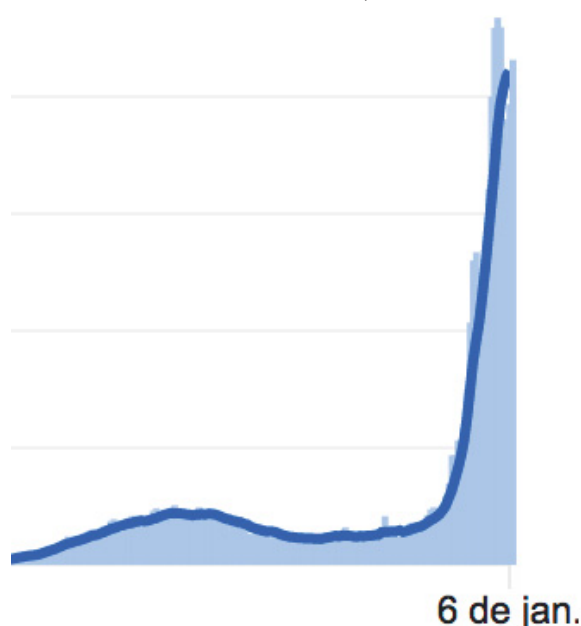
This may be interpreted as a form of narrative, as the information moves across time and leaves the interactor with an idea of structure and what to anticipate (WEBER, 2020). The structure might possibly be a positive element to have in a DV. It has a chance of fostering agency as the interactor sees the future as clearly predictable and feels in control of the situation (EICHNER, 2014; WEBER, 2020).

However, this narrative could also come to foster fear in the interactor. Despite the colors being soothing and cooling, the messages might turn frightful when the interactor sees the numbers rising so rapidly and suddenly. For example, in figure 83, there is a sudden spike in cases.

Because of the position of the lines and the bars, the DV implies that the wave will get bigger. This could possibly make the interactor react out of fear, triggering death anxiety (GRANT; WADE-BENZONI, 2009).

In this case, the bars and lines are the mortality reminder, as they are the elements to which the concept of death is anchored (GREENBERG; ARNDT, 2012; ROSENBLATT et al., 1989; VON ENGELHARDT, 2002). If they grow so suddenly, the mortality reminder is quick and arrives fast, related to death anxiety.

FIGURE 83 – GOOGLE DV, SUDDEN SPIKE



SOURCE: Google. Coronavírus (COVID-19) Search page. Available on: Google. Accessed: 08 Jan. 2022.

In conclusion, the DV makes good use of simplification and provides the interactor with a good summary of what the situation of COVID-19 is like. However, it tries to be so neutral that it could be used for anything. The data content does not appear at any moment, thus making the DV generic enough to represent anything.

Additionally, it borrows elements from traditional statistical time charts that might not adapt well with the context of death behind it (HEPWORTH, 2016). This causes some graphic choices that might potentially have anxiety-inducing meanings. The most striking visual elements and their connections with death awareness are presented in CHART 16.

CHART 16 – RELATION BETWEEN VISUAL ELEMENTS AND DEATH AWARENESS,
GOOGLE

Visual elements	Death awareness	How it happens
Blue bars	Anxiety	Syntactic • Syntactic structures: clustering, aligning, anchor to space • Syntactic role: point locator Semantic • Correspondence: Literal • Informational role: informational object Elements of engagement • Sequence • Temporal dimension
	Reflection	Syntactic • Visual attributes: color
Blue line	Anxiety	Elements of engagement • Narrative: sequentiality

SOURCE: the author

9.3 GYRO

9.3.1 Syntactic

The most prominent graphic element for this DV is the cluster of crosses. However, they are not being seen as individual elements. Instead, the DV prioritizes the view of the crosses as a single clustered unit. Because the crosses are so neatly organized with very little space between them, their cluster creates a single visual element. This means the interactor has a chance of seeing a block of crosses arranged similarly to a cemetery (VON ENGELHARDT, 2002).

Unlike the other two DV, the concept being anchored here is not just death but the death of a person. Each cross and the space it occupies in the digital landscape anchors the death of a unique individual. The idea that each death is of a unique individual could be preserved for this visualization.

Crosses might cause death anxiety, as they foster guttural, visceral, and immediate responses to their conventional relationship to death and tragedy (GRANT; WADE-BENZONI, 2009; METCALFE; MISCHEL, 1999). Because the DV employs many reminders of death, it could potentially cause the interactors to become afraid and rely on self-protective measures, as per

TMT and TMHM (GOLDENBERG; ARNDT, 2008; GREENBERG; ARNDT, 2012; PYSZCZYNSKI et al., 2020; ROSENBLATT et al., 1989).

The DV uses only neutral colors. The background is muted beige, focusing on the black crosses. However, the title of the DV can come to attract too much attention. The text is bolded and much bigger than the rest. Despite that, there is little graphic work on it. The title only tells the interactor what the crosses are and provides the total number of casualties, but it calls for much attention to how big and bold it is.

9.3.2 Semantic

This DV is a clear metaphor for a cemetery. The crosses use metaphors and arbitrary conventions to signify tombstones (VON ENGELHARDT, 2002). Walking through a graveyard ranks second in mortality reminders that cause death anxiety, only losing to the fear of dying (NEIMEYER, 1997). Therefore, this DV might incite fear in the interactors and trigger the more self-protective nature of TMT and TMHM (GRANT; WADE-BENZONI, 2009; GREENBERG; ARNDT, 2012; PYSZCZYNSKI et al., 2020; ROSENBLATT et al., 1989).

Additionally, how they are arranged in a grid parallels imitates real-life cemeteries (figure 84). For example, the Arlington Cemetery has rows upon rows of graves for the U.S. military (figure 85). Germany's Memorial for Murdered Jews of Europe has staked gravestones for each Jew murdered during the holocaust (figure 86).

FIGURE 84 – GYRO DV AS A CEMETERY



SOURCE: GYRO 4life. Available on:

<https://4life.gyro.ct.utfpr.edu.br/?fbclid=IwAR05siUtd54010NqvW-FgrnHmVvrFCitiANyYSmlWBXEO_m6-M857sOgykg#>. Accessed: 20 December. 2021.

FIGURE 85 – ARLINGTON CEMETERY



SOURCE: whistleblower. The Triumph and Validation of Arlington National Cemetery Whistleblower Gina Gray. Available on: <https://whistleblower.org/uncategorized/the-triumph-and-validation-of-arlington-national-cemetery-whistleblower-gina-gray/>. Accessed: 08 Jan. 2022.

FIGURE 86 – MEMORIAL FOR MURDERED JEWS OF EUROPE



SOURCE: Yahoo! News. Dark tourism memorial sites will help us heal from the trauma of coronavirus. Available on: <https://news.yahoo.com/dark-tourism-memorial-sites-help-104943757.html>. Accessed: 08 Jan. 2022.

Cemeteries are organized in a grid, so finding the people buried becomes easier. Because the DV traces a direct parallel between the visual representation and the real world, each digital location is also anchored to a specific person (VON ENGELHARDT, 2002). Because of this, the grid system of the DV could potentially give each death – each person – their unique place in the representation. This might make each death unique.

In addition, the crosses are precisely the same, representing a life. This uniqueness in the representation might preserve the value of each life lost and come to foster death reflection since it triggers the pro-social aspects

of contemplating mortality (GRANT; WADE-BENZONI, 2009; LYKINS et al., 2007). When people are confronted with individual stories and feel the weight of individual death, they might become more engaged and willing to improve their communities' lives (COOLEY, 2020).

9.3.3 Classification of graphic representations

This DV functions in a very similar way to a picture or a simulation. The focus is not the numbers or the data but the content. The creators of the DV, much like photographers, chose to present the data as a metaphor for a cemetery, which seeks to highlight the heaviness of the content of the data over the possible analytical purposes of a DV (COOLEY, 2020; GRAY, 2020; HEPWORTH, 2016).

9.3.4 Elements of engagement

The DV's scrolling suggests the interactor moving through the graphic space as a cemetery (BIZZOCCHI, 2003). Because of the size of the DV, it is common to get lost in the rows and rows of crosses, and, at that moment, the interactor could potentially realize the scope of the tragedy that COVID-19 was and still is.

The scroll bar on the right side of the DV gives the interactors an idea of how far down they scrolled and how much more there is to go. It provides perspective and highlights how many deaths were (VON ENGELHARDT, 2002).

The cursor represents the self-inside of the DV. As the interactors scroll through the page, their fingers do what their legs would be doing in the real world. The cursor is not just a simple tool but a conduit for the interactor to manipulate the DV, which might foster control and engagement (BIZZOCCHI, 2003).

In conclusion, despite the simplicity being used in this DV, the way the graphical elements were conceived has a higher chance of preserving the content and context of the data. Unlike the JHU and the Google DV, this DV seems to place death as the center of attraction. It is likely not a

representation that could be read without the interactor realizing the tragedy behind the data (COOLEY, 2020; HEPWORTH, 2016). CHART 17 summarizes the most striking visual elements and their connections to death awareness.

CHART 17 – RELATION BETWEEN VISUAL ELEMENTS AND DEATH AWARENESS, GYRO

Visual elements	Death awareness	How it happens
Crosses	Anxiety	Syntactic • Visual attributes: shape • Syntactic structures: lineup • Syntactic role: point locator, grid Semantic • Correspondence: Literal, metaphor, metonym, arbitrary convention • Informational role: informational object
	Reflection	Syntactic • Syntactic role: point localizer, grid Semantic • Correspondence: Literal, metaphor, metonym, arbitrary Convention • Informational role: informational object Elements of engagement • Narrator (scroll-telling)

SOURCE: the author

10 CONCLUSION AND FINAL CONSIDERATIONS

This chapter discusses the main conclusions drawn from this study. First, the objectives are presented and how they answer the main objective. Following, the limitations of this study are discussed, and lastly, the contributions and future developments are presented.

10.1 MAIN CONCLUSIONS

The main conclusion drawn from this study was the SSCE framework which provides valuable insight into how designers analyze and describe data visualizations that represent death.

The SSCE framework focuses on possible connections between modes of representation and death awareness. The framework highlights graphic elements that are common in data visualizations. For example, JHU used many features from the Google maps to create their statistical map, despite not adding much to the representation or confusing the interactor at some points. Google presented data in the same way any chart would have, without much regard for the represented content (i.e., death).

When visualization borrows the graphic elements of its genre, it simplifies the content to the level of meaninglessness. Furthermore, both the JHU and the Google DVs are so highly used for other purposes (i.e., graphs being used for the stock market and maps for shipment information) that it loses the weight of the content representing data about death. Therefore, these visualizations transform human loss and grief into numbers, removing the meaning and sorrow.

Using templates to represent death might impose additional elements that foster death anxiety. Google DV, discussed in chapter 5.2, uses a traditional statistical time chart. Still, in the context of contagion and death, any rapid increase or dip in the data can foster strong emotions. This is clear when the numbers rapidly increase as represented in DV.

The rapid increase does more than inform. It might foster fear and anxiety because of the context around the data. However, Google deals with

this data the same way it would have any other data type, reutilizing a standard template.

Different types of visualization foster different reactions. The more artistic approach used by GYRO is not superior or inferior to the data-driven approach favored by Google and JHU, but they do serve other purposes.

If a representation uses too many elements that foster emotional responses, it risks inciting fear and triggering self-preservative and aggressive behavior. On the other hand, if the DV veers too far on the side of data accuracy, it might make interactors lose engagement and believe their actions have no real consequence.

The SSCE framework allowed the researcher to infer that Data-driven DVs, like Google, seems adequate for representing complex data. Moreover, they can be conveyed straightforwardly, allowing the interactors to find patterns and prepare themselves for the future.

On the other hand, emotionally engaging DV, like GYRO, is necessary to highlight the tragedy of the content to allow people to engage in behavior that can benefit healthy lifestyle changes or positive pro-social outcomes.

Therefore, the SSCE framework presented has the potential to enable the researcher to assess data visualizations beyond only superficial elements.

10.2 OBJECTIVES REACHED

This research had three secondary objectives. The first was to “establish how designers use graphic elements to create data visualizations,” which was achieved through a literature review that mapped out frameworks to dissect data visualizations. The results corresponding this goal, are presented in chapters 2–5.

The second objective was to “map out how data visualizations have been used to represent death of the COVID-19 pandemic”, which was achieved through the analysis proposed in phase 2 of the close reading method. The results of this goal are presented in chapter 8.

The analysis of the selected sample of DV traced connections between the modes of death representation in the data visualizations and death awareness. The results for this objective were discussed in chapter 9.

The literature review allowed the first draft of the descriptive-analytic SSCE framework for mapping out how the visual elements in data visualization foster death awareness. The analysis of 3 DVs allowed iteratively refine the SSCE framework to answer the main objective.

10.3 STUDY LIMITATIONS

The size of the sample was a limitation of this study. The sample size could be considered a limitation, as many graphic elements in other DV were not explored. For the analysis of the DV to be deep enough, less DV had to be analyzed. A greater quantity and variation of DV should be analyzed for future studies.

Another limitation was the number of researchers that tested the SSCE framework. Due to time limitations, only the creator of the framework managed to test it to analyze data visualizations.

10.4 CONTRIBUTIONS AND FUTURE DEVELOPMENTS

This dissertation sought to contribute to the growing body of literature about data visualization and its effects on human behavior and perception, especially when dealing with data that triggers any form of death awareness.

The SSCE framework guides the analyses of DV to outline their purpose best. Although it was refined using Covid-19 data visualization, it has the potential to be applied to different data.

Future developments should focus on further mapping out other types of DV to see if design elements that were not included in this project include mortality reminders. Furthermore, the next logical step to this research is to use interactor tests to verify this dissertation's findings. Using the results presented here, a testing protocol could be developed to test DV and map out how interactors perceive their death awareness when confronted with data visualizations about COVID-19. Additionally, the SSCE framework should be

tested with a panel of specialists to assess the feasibility of using it to analyze data visualization by designers.

The SSCE framework presented here has the potential to span further discussions in the field of design and allow researchers to begin to think about what the visual elements do to the people that use the artifacts they design.

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