Utrecht University

Department of Information and Computing Science

Applied Data Science Master's Thesis

Conflicting Wavelengths

Visual Semiotic Analysis of Corporate and User-Generated Imagery on 5G technology

Image: Tumblr, 2023

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July 5, 2024

Abstract

During the COVID-19 pandemic, the spread of conspiracy theories linking the virus to 5G technology sparked a global phenomenon of telecom tower vandalism and protests. Content posted on social media can heavily influence and shape societal beliefs and actions. Given the constant stream of new material posted online, this research aims to contribute towards two different fields of knowledge. Once, towards the visual semiotic aspects in the online debate about 5G technology, focusing on the representation of meaning in corporate produced images and user-generated images on Tumblr. Twice, towards the methodological exploration that aims to find a suitable framework and fitting computational methods for a data-scientific approach to visual semiotics. By applying and expanding the 'Unity of Semiotics' framework by Charles Morris, which encompasses syntax, semantics, and pragmatics, this study analyses differences in how 5G technology is visually encoded by corporate entities and decoded by media audiences on Tumblr. Results reveal that corporate imagery is encoded to instill calmness and low dominance through a brighter and more uniform color palette that focuses on human elements. In contrast, Tumblr content is more diverse, vibrant, and technologically oriented, reflecting engagement in communication. Accordingly, it contributes to understanding the role of visual semiotics in shaping public discourse and perceptions of 5G technology.

Key words: Visual semiotics, computational methods, digital humanities, data science, conspiracy theories, 5G technology, user-generated content

Contents

1. Introduction

“Turn off your cell phones on October 4th. The EBS is going to "test" the system using 5G. This will activate the Marburg virus in people who have been vaccinated. And sadly turn some of them into zombies” (gina shirah [@GinaShirah81815], 2023; Klee, 2023).

During the COVID-19 pandemic, news outlets worldwide frequently reported acts of vandalism involving telecom towers catching fire. This new phenomenon was caused by rapidly spreading conspiracy theories that linked the coronavirus to 5G wireless technology. In the month of April 2020, the conspiracy theory had resulted in more than a hundred incidents in the United Kingdom alone (Satariano & Alba, 2020). Even though multiple scientists have explained that it is biologically impossible to transmit the virus or reduce defenses to it via 5G mobile phone signals, the rumors were going global (Goodman & Carmichael, 2020). Conspiracy theories play a significant role in the viral spread of misinformation and have a significant impact on public opinions about certain topics. The theories connect different events that have taken place at various times and places and involve several actors that do not seem to fit together to bystanders (Madisson & Ventsel, 2020).

The spread of COVID-19 caused substantial changes in the lifestyles of communities worldwide. More than 180 countries had recorded 24 million positive cases by the end of August 2020. The World Health Organization declared COVID-19 a pandemic due to its alarming level of global spread (Siriwardhana et al., 2020). Simultaneously, the use of 5G technology was growing to support in the surge in demand for smart electronic devices and wireless multimedia that created a burden on already existing networks. Compared to 4G networks, 5G communication was innovated to solve issues and provide higher data rates, larger capacity, and better latency (Ahmed et al., 2020). The need for 5G innovation also indicates the growing habits of individuals spending their lives online. The arrival of social media has had a substantial impact on how people access information and interact online. Users tend to acquire information they like, filter out information they do not like, and join groups of like-minded people. According to polarization theory, this can act as a mechanism to reinforce existing opinions, moving entire groups towards more extreme positions (Cinelli et al., 2022).

This study is involved with the everchanging process of information retrieval. The sending and receiving processes of visual messaging will be analyzed through a newly shaped theoretic and methodological framework for visual semiotics. The central question guiding this research is: *How do the visual semiotics of 5G technology imagery differ between corporate-produced content and user-generated content?*

Conspiracy theories are defined as ‘alternative explanations of historical or ongoing events claiming that people or groups with sinister intentions are engaged in conspiratorial plotting’ (Mahl et al., 2023). For a long time, conspiracy theories were perceived as ‘soft beliefs’ and harmless phenomena. Only recently, these theories changed into extremist beliefs as a result of changes in media that enabled faster communication and the spreading of misinformation (Mahl et al., 2023). This phenomenon has sparked scientific interest in the online dissemination of messages.

One way to do research on the exchange and interpretation of messages is through semiotics. Semiotics is concerned with how representation generates meaning (Curtin, 2009). Thus far, research has touched upon the theory of semiotics for textual analysis. Over the years, there has been a shift of attention towards visual messages on social media. Sharing images is becoming an integral part of the social media experience, and are a large factor in spreading information online (Grusauskaite et al., 2022; Russmann & Svensson, 2017). The shift from text to images is also applicable in the sharing of conspiracy theories. As image analysis techniques improve, it is interesting to shift the emphasis from textual semiotic analysis to visual semiotic analysis.

Earlier research in the visual semiotic field, for example, performed detailed analysis on the messages and visual metaphors in political cartoons, aiming to portray the tools used to convey these messages and their role in the ongoing war of ideological misrepresentation (Mazid, 2008). Another study examines how emotive meaning is represented in visual images using facial expressions and body orientation as semiotic resources (Feng & O'Halloran, 2012). Thus far, the field of visual semiotics has focused on the detailed analysis of individual images or small manually annotated datasets. Given the substantial number of images that are posted on social networking sites every day, this research advocates for a data-scientific approach to visual semiotics.

Building upon Stuart Hall's transmission model of communication, this study aims to portray differences in delivering messages and meaning-making online through a visual comparison between the images shared by two groups of people with a sender and receiver relationship. Hall's transmission model posits that a sender transmits a message to a receiver. This receiver interprets the message based on their own context and experiences, which may differ from the sender's intended meaning (Hall, 1973). I compare 5G-related images shared by corporate entities promoting the beneficial and harmless aspects of 5G networks with images shared on the visually-heavy social networking site Tumblr. The study attempts to form a methodological framework that can manage a large dataset of images. I formulate a framework for scientific analysis of semiotic data by dividing semiotics into syntax, semantics, and pragmatics. The division permits the use of automated algorithmic and computer vision methods to generate insightful data from images. The data is used for quantitative analysis and qualitative interpretations, contributing to a viable solution for large-scale data research.

2. Theoretical Framework

Semiotics involves the study of any element that can be considered a sign (Aiello, 2020). These signs can be drawings, paintings, or photographs, but they also include words, sounds, and body language (Chandler, 2022). Throughout the years, many scientists have written about the field of semiotics and its broad definition, making it challenging to offer a simple definition. Therefore, it is important to limit the definition to a suitable frame for this research. The specific focus of this research is visual semiotics in still images. Visual semiotics should be considered a sub-field of semiotics (Aiello, 2020). To explain the theoretical and methodological perspective behind visual semiotics, the foundation of the theory of semiotics, in the broadest sense, is of first importance. The subsequent paragraphs delve into the evolution of visual semiotic analyses and cultural analytics, offering context and explaining how these factors influence the decisions made in developing a new methodology for applying data science to visual semiotics.

<u>Foundation of semiotics</u>

In *Foundations of a Theory of Signs*, Charles Morris (1938) tries to ensemble all previous studies of signs to form a 'theoretical structure […] to embrace the results obtained from different points of view and to unite them into a unified and consistent whole'. The theory provides a framework for understanding how signs function in communication. It is important to clarify that semiotics serves both as a theory and methodology, applicable to various 'texts', such as novels, paintings, films, buildings, and websites (Aiello, 2020). Here, 'text' refers to any semiotic object with material or symbolic boundaries and structural independence, or where different parts all have a function in relation to a 'whole' and thus can be examined as a unit (Aiello, 2020). In Charles Morris' theory of signs, semiotics has been divided into three branches: *Syntactics* is the study of 'the relations of signs to one another.' It is about the rules governing how signs can be put together to form meaningful units. It functions as a structural framework within which signs operate (Morris, 1938). For example, the order of words in a sentence. *Semantics* is the 'relation of signs to the objects which they may or do denote.' It's about the meaning behind signs and deals with the connection between a word and the concept or object that it refers to (Morris, 1938). For example, the word 'horse' represents a large mammal with four legs and hoofs. Semantics is concerned with understanding how signs convey meaning and how different signs can represent the same thing. *Pragmatics* is the 'relation of signs to their interpreters.' It focuses on the use of signs in communication contexts and the effect they have on people. It considers context, intention, and interpretation. Pragmatics examines the use of signs to accomplish specific communication objectives and their interpretation by various individuals or groups in various contexts (Morris, 1938). For example, the meaning of a word or gesture can vary depending on the cultural context or the speaker's tone of voice.

Together, these three branches form the 'Unity of Semiotic.' According to Morris, 'only those terms are semiotical which cannot be defined in any of the component fields alone' (Morris, 1938). Within semiotics, *syntax*, *semantics*, and *pragmatics* provide a framework for analyzing and understanding signs and their role in communication. After explaining the fundamentals, a more visually specific approach to semiotics emerges, still taking into account Morris' foundations.

The Treachery of Images

Researchers are increasingly using visual semiotics, a sub-field of semiotics, to examine visual texts like images (Aiello, 2020). To describe the thought behind visual semiotics, I will use René Magritte's painting '*La Trahison des Images,'* or *'The Treachery of Images'* as an example.

Figure 1: Magritte's La Trahison des Images (1928). Source: Wikipedia

Magritte depicts a pipe with the phrase '*Ceci n'est pas une pipe'*, or *'This is not a pipe'* painted underneath (Figure 1). Magritte stated that he would have been lying if he had written *'This is a pipe'* below his picture of a pipe, as the painting is just a representation of a pipe. This proves that signs are not the same as what they represent (Aiello, 2020). To make sense of the world around us, we systematically rely on signs (Chandler, 2022). Semiotics helps us understand how imagery and language do not reflect reality but contribute to constructing it (Aiello, 2020).

Foundations of visual semiotics

Visual semiotic analysis aims to reveal the hidden structures, cultural codes, and dominant meanings in images (Mannay & Pauwels, 2019). By doing this, visual semiotics is a powerful tool for systematically studying and critiquing the ideology behind visual communication. The current challenge is that visual language does not share the same privileged position in the scientific field as written and verbal linguistics. This is what art critic Fernande Saint-Martin states in her book *Semiotics of Visual Language* (1990). After recent literature research, the lack of complete and consistent visual language theories and methods implies that Saint-Martin's statement of 1990 still stands. Visual language has been defining its own theories and objects of study without the ability to build on a long tradition of theory and practice (Saint-Martin, 1990).

Two scientists who laid the foundations for visual semiotic theories are Charles S. Peirce and Ferdinand de Saussure. They developed their 'theories of signs' independently, but around the same period of time (Aiello, 2020). Peirce's typology of signs theory distinguishes between signs that clearly connect their form and meaning, and conventional signs that derive their meaning from societal agreements rather than inherent resemblance (Peirce, 1932). Where Peirce's theory mostly focused on the referential, Ferdinand de Saussure focused on the structural and relational. Saussure incorporated social life into his theory of signs. The language used to describe a phenomenon not only communicates existing perceptions, but also actively constructs and molds our perceptions, beliefs, and discussions about various topics (Aiello, 2020; Saussure, 1983).

Saussure's theory of sign only applied to verbal language, not to visual language. However, it played a big role in developing the conceptualization of meaning tied to cultural and social influences. Therefore, his approach has been widely applied in cultural theory and visual analysis (Aiello, 2020). Peirce's and Saussure's typology of signs marked a start in understanding how visual perception interacts with culture and meaning-making.

Methodological influences of Roland Barthes, Jean-Marie Floch, and Lev Manovich

Building on Saussure's structuralist theory, visual and social semiotics were brought to life. Roland Barthes was the first to perform a systematic look at non-linguistic signs. Barthes was interested in how meaning changes across historical and cultural contexts. He claimed that visual meaning can be broken down into two categories: denotation, which is the literal meaning of an image, and connotation, which is the symbolic or ideological meaning. An example is an analysis of a pasta brand's advertisement. The denotative meaning is a '*fishnet shopping bag full of packaged pasta, canned tomato sauce, onions, peppers, and mushrooms, together with a packet of grated cheese, a tomato, and a mushroom next to the bag, all of this being displayed against a red background'*. The connotative meaning is that of *Italianicity*. This ad displaying the 'essence of being Italian' would work for the French public, whereas Italians might not associate the connotation of *Italianicity* with the elements in this message. The ideological meaning is therefore context-dependent (Aiello, 2020). In the following years, Barthes and his junior, Jean-Marie Floch, introduced several additional layers to visual semiotics, all with their own special focus. These additional layers are the key to a social semiotic understanding of visual analysis (Aiello, 2020).

A main limitation of semiotics is its focus on solely analyzing texts and their elements, often overlooking the practical methods and processes that are involved in creating or interpreting the text (Aiello, 2020). In specific historical, cultural, and institutional contexts, social semiotics explores the use of semiotic resources and how individuals discuss, plan, teach, justify, and critique them (van Leeuwen, 2005). Furthermore, the theory examines the political implications and ideological underpinnings of semiotic choices that become naturalized over time and are thus often accepted and taken for granted without further questioning (Aiello, 2020). Walking, for example: It is thought of as non-semiotic behavior and something that we have in common with other species, but there are many ways of walking. Social institutions, such as the fashion industry, the army, and the church, have developed their own ways of walking (van Leeuwen, 2005). Social semiotics sees meaning-making as a process deeply rooted in existing cultural norms and influenced by social structures, whereas visual semiotic theories specifically focus on how meaning is constructed and communicated through visual means (Aiello, 2020).

While Barthes and Floch provide deep insights into the way individual visual signs construct meaning within cultural and social contexts, Lev Manovich designed methods that are able to study larger corpora of visual signs starting in the early 2000's. The goal of his method is to form an understanding of how digital and new media reshape our cultural and social landscapes (Manovich, 2001). Although Manovich does not focus extensively on visual semiotics, his work often intersects with semiotics as he analyzes how media and technology communicate and represent information (Dondero, 2019). His methods are situated at the intersection of data science, media studies, and digital culture studies (Manovich, 2020). Different from most visual analysis in the field of media studies, his methods are designed for large datasets using computational and visual methods. Visual semiotics focuses on close reading, while Manovich's '*Media Visualization*' focuses on distant reading (Dondero, 2019). He designed Media Visualization as a tool for visualizing massive datasets, showing the corpus in its entirety (Dondero, 2019). Manovich draws the distinction between Digital Humanities and Media Visualization. In the Digital Humanities, the images go through a process of disembodiment to be visualized. This results in a loss of the ability to visualize an original collection of images. Reduction of the corpus is involved to reveal patterns (Manovich, 2012). Media Visualization translates pictures into pictures. Visualizations reveal new patterns by showing the whole image collection, providing a distant view (Dondero, 2019; Manovich, 2012).

These foundational perspectives provide essential insights and contextualize the evolution of semiotic analysis. However, after discussing these theories, I will revisit the semiotic framework, which Charles Morris (1938) divided into syntax, semantics, and pragmatics. Traditionally, visual and social semiotics have concentrated on analyzing individual images, a focus that does not align well with the demands of data science and the analysis of large-scale datasets using computational methods. Lev Manovich's methods, while designed for large-scale datasets, do not specifically cater to visual semiotic analysis. Therefore, adopting Charles Morris' semiotic framework offers a better approach for this research, adjusting his work with additional influence and inspiration from Manovich's methods. I will consider the principles of visual and social semiotics theory when choosing computational methods and theories to interpret the results. Building upon this framework, I will develop my own visual semiotics methodology that aligns more closely with the needs of data science research. Further reasoning for this decision will be explained in the next chapter.

3. Methodology

The challenge in this research lay in finding a methodological framework that was suitable for a large dataset of images. In order to find an answer to the research question, a new method needed to be designed. Therefore, this research is exploratory and aims to take a first step in forming a data-scientific approach to visual semiotics. Traditional visual and social semiotics have focused on the analysis of individual images, which does not align well with the requirements of data science. Visual and social semiotic theories emphasize the social and cultural dimensions of meaning-making. The detailed type of analysis applied to individual images provides a nuanced and comprehensive understanding of social and cultural dimensions. It would not have been responsible or fair to extend this level of detailed analysis to a large dataset and define culture and social phenomena by the numeric mean of the whole set. This would have diluted the precision and depth that the theory demands and did not align with the goal of this research to draw conclusions about the difference in visual portrayal between two large groups of data. Social semiotics is best applied with caution and care, which is not feasible with large-scale quantitative analysis. The Media Visualizations methods of Manovich are designed for the analysis of large-scale datasets but are not traditionally intended for visual semiotic research. Therefore, it is partly, but not entirely, usable as a research method.

Charles Morris' framework, splitting up semiotics into syntax, semantics, and pragmatics, offered a more suitable data scientific approach for this semiotic analysis while still considering the underlying meaning-making processes, and leaving room for Media Visualization. Morris' framework allowed for a structured analysis that could accommodate both quantitative and qualitative research methodologies. Visual syntax and semantics contain characteristics that are suitable to be analyzed quantitatively in large amounts of data, with room for qualitative interpretations. The pragmatic approach then facilitated the possibility of using the results from the syntactical and semantical methods as building blocks to form qualitative insights. Stuart Hall's (1973) Encoding and Decoding theory provided an additional layer for pragmatic qualitative reasoning in understanding how meaning was constructed and interpreted within technological contexts.

In this thesis, I used a mixed methods research approach by integrating both quantitative and qualitative methodologies to perform explorative research. This approach allowed for a thorough analysis of the research question: How do the visual semiotics of 5G technology imagery differ between corporate-produced content and user-generated content? To answer this question, I divided the semiotic analysis into three sub-analyses that each contained their own quantitative and/or qualitative characteristics. Using Charles Morris' Unity of Semiotics, the first sub-analysis was a visual syntax analysis.

Syntax

According to art critic Saint-Martin (1990), the syntactic rules of the visual language are made up of operations and functions that help our perception connect basic elements in different visual fields. Using syntactical rules can help create specific spatial arrangements. She describes that the visual field is like a force field where certain energies produce different effects, leading to various types of spaces. The energies originate from light reflections and can be broken down into basic visual units called *coloremes*. Coloremes are units that are not fixed and exist before visual variables, but are created and transformed along with them (Saint-Martin, 1990). In other words, coloremes are considered the smallest units of color perception in a visual field, the phonemes of the spoken language, serving as building blocks for visual information.

In this study, I adopted Fernande Saint-Martin's theory of visual syntax, specifically her concept of coloremes, as a framework for my syntactical methodological approach. Saint-Martin's notion of coloremes as the fundamental units of color perception aligns well with the way digital images are composed of pixels as the smallest unit of a digital image. This way, I was able to analyze visual syntax by looking at the color-specific relationship between pixels. By drawing this parallel, I employed the analytical technique of K-means color clustering.

K-means clustering was used to group pixels of an image based on color similarity and clustered the colors within the image (see Python code in Appendix B). This process allowed me to organize and quantify the representation of the color palette of the complete datasets. I used Manovich’s Media Visualization method to reveal new color patterns with visualizations that show the whole image collection. Next, a Digital Humanities approach was used in the form of descriptive analysis. The images underwent disembodiment and were reduced into numbers that could indicate if means of the datasets were significantly different. By integrating Saint-Martin's theoretical perspective with this digital image analysis technique, I aimed to perform a syntactical analysis that bridged visual theory and computational methods.

Semantics

For the semantic analysis of the results of the color analysis, I consulted research on the effect of color on consumer perceptions by Labrecque and Milne (2012). This paper contains studies that provide a framework for the interpretations of the syntax color results when it comes to color psychology and associative learning. Using this study as a framework helps understand the emotional and psychological responses brought out by different colors and brightness. The images in the corporate and Tumblr datasets are aimed at communicating distinct messages and evoking responses from viewers. I moved away from cultural interpretation and symbolism since this subject is too complex for the matter of this research and requires detail and nuances that I’m not able to provide considering time constraints. Therefore, I’m staying within the boundaries of the psychological color effects of the research by

Labrecque and Milne.

For the second semantic analysis, I detected objects in the images using the Ultralytics YOLOv8 pretrained model (see Python code in Appendix B). Once the model detected an object, it was involved in giving meaning to the object, thus engaging in semantics. I did not pretrain the model on my dataset due to time constraints. I performed a Human-Computer Agreement (HCA) test on the detected objects that were relevant for my analysis. I hand-labeled 30 randomly selected images, 15 from the corporate dataset and 15 from the Tumblr dataset, on 'humans' and 'technology that has a screen'. I compared this with the object detections of the YOLOv8 model and got 96% accuracy on detecting humans and 90% accuracy on detecting technology (see Appendix A, Table A1). I concluded that the results were sufficient for the purposes of this study.

To analyze the ratio between people and machines in the images, I used the object detection model, which performed well in detecting people and technology-related items such as laptops and phones. I performed word frequency analysis on the results to examine the frequency of the categories humans and technology across the datasets. This is in line with the methods of Digital Humanities where disembodiment of the images takes place to form conclusions about large-scale corpora.

Pragmatics

Stuart Hall's Encoding and Decoding Theory offered insights into how audiences interpret and make sense of media messages (Hall, 1973). It explores the dynamics of communication and reception within mediated environments such as the internet and social media platforms. Encoding involves the process by which creators of visual content embed messages and meanings into their images and media. Decoding refers to how audiences interpret and understand these visual messages. These messages can vary widely based on individual perspectives, cultural contexts, and the socio-technical environment in which the media is consumed.

I applied Stuart Hall's Encoding and Decoding theory to analyze the pragmatics of the dataset. By using this theory, I aimed to incorporate the outcomes from the syntax and semantics analyses to provide insights into the pragmatics of the corporate and Tumblr datasets. I viewed the corporate messaging as the 'encoding' entity and the user-generated Tumblr messaging as the 'decoding' entity.

Trials and potentials

During the explorative phase, I attempted GLCM feature extraction for texture analysis and pixel-to-pixel relationships in the context of syntax analysis. My intention was to add meaning to the semantic analysis. GLCM features, on the other hand, are primarily used for preprocessing in computer vision, and not much meaning has yet been assigned to them in a semiotic context. Due to time constraints, I decided to skip this method, although I believe there is semiotic potential in the idea.

To classify more detailed image descriptions, I also experimented with image classification models instead of image detection models. Unfortunately, this approach resulted in many false results.

While the results were relevant in the sense that the classification model gave results in the correct domain of objects, they were too inconsistent and unreliable to add to the semantic analysis. To ensure a sufficient analysis, I decided to focus on color clustering and object detection. The final process is depicted in the flowchart in Figure 2.

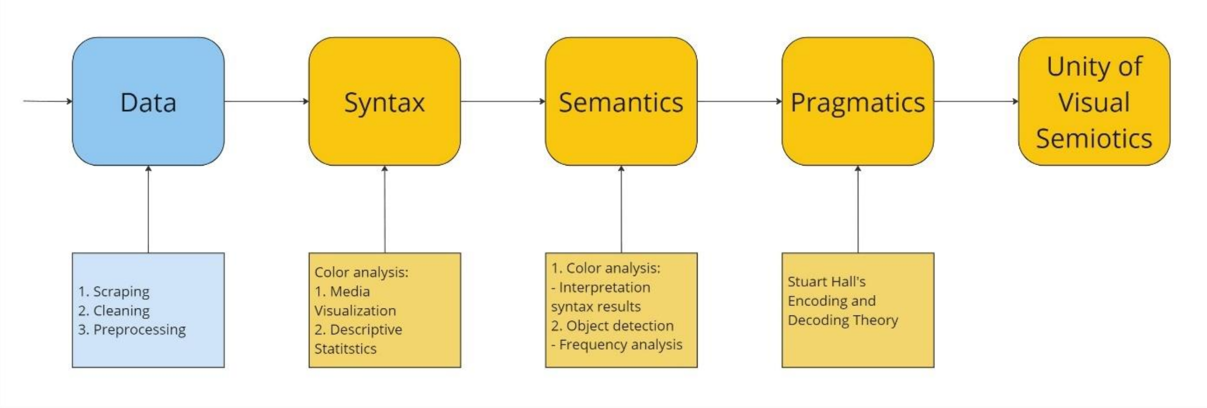

Figure 2: Flowchart of Methodology

<u>Tumblr</u>

Tumblr is the second-most dominant blogging site in the United States. Unlike other microblogging services like Twitter, Tumblr does not have a character limit on posts, allowing for more comprehensive and nuanced content. Additionally, Tumblr has a strong image presence and supports various multimedia formats, which is critical for a visual analysis of 5G representation. Unlike Facebook, the platform has a unidirectional social network structure. This means that users can view content and follow other users without having to request access. Next to this, the ability to reblog posts facilitates the spread and visibility of content and provides a rich dataset for examining user-generated discourse. Tumblr is easy to register and does not differentiate between verified and non-verified accounts (Chang et al., 2014). One can sign up with a valid email address but does not have to reveal their identity, promoting people to speak more freely in anonymity (Scott, 2004). Compared to other image-sharing sites like Flickr, Tumblr's reblogging feature enhances content interaction and distribution, making it a more dynamic environment for studying visual and textual narratives around 5G technology (Chang et al., 2014).

<u>Tumblr dataset</u>

Using the Tumblr API, the Tumblr images were scraped (*Tumblr API*, n.d.). A script was coded to scrape the images' hyperlinks, as well as other metadata such as blog names, dates, tags, and blog text. The data was then saved in CSV format. Images were downloaded using Python requests (see Python code in Appendix B).

For the selection of Tumblr blogs to be scraped, the 'Tagged Method' from the Tumblr API was utilized. To determine the hashtags used for scraping the blogs, small explorative research was conducted beforehand on the social networking website. The goal was to compose a set of hashtags that captured the wide spectrum of discussions surrounding 5G on Tumblr, ranging from conspiracy theories to futuristic art to technical discussions. I relied on the affordances of the search function to select the corpus of key words. Based on this research, I selected ten hashtags: #5G, #stop5G, #5Gconspiracy, #5Gcoronavirus, #5Gdangers, #5Gnetwork, #5Gtechnology, #5Gtowers, #5Gwarning, and #dangersof5G.

A target of approximately two thousand images was set, as this was a comparative size with the corporate image dataset used for this research and is a sufficient size for data scientific research. The data collection period spanned from November 2019 to April 2022, covering the COVID-19 pandemic and the launch of 5G services.

Due to limitations in the Tumblr API, location information could not be retrieved. Regarding language, the dataset mainly consisted of English content, but other languages were also included. The dataset was not specific to any particular language.

Corporate dataset

The dataset used for this analysis was collected by the Digital Methods Winter School (Oever et al., 2021). Initially, the DMI Winter School performed a close reading of a hand-picked selection of web pages dedicated to 5G on the websites of key companies. The list of companies was compiled by a researcher with experience in 5G governance, ensuring a thorough understanding of relevant stakeholders. Using the Instaloader Python module, the DMI Winter School scraped all posts from six companies' Instagram accounts. Following this, a second script was employed to gather all posts containing the hashtag #5G in their descriptions. Additionally, the DMI Winter School used the Qwant search engine to query images located under the domains of vendor companies (Oever et al., 2021) and downloaded the hits using a script. The images were posted between 2015 and 2020.

Data cleaning

After organizing the data into Excel CSV files, Tumblr blogs without images were removed from the dataset. Additionally, duplicates were identified and deleted using the Visipics program from both datasets. These duplicates included not only commonly used images, but also reposts or double-scraped images. I was unable to identify the cause of the duplicates, so I decided to delete all duplicates. Further cleaning included the removal of unsupported file formats, such as GIFs and web files. Images dating back to 2011 were also specifically removed from the Tumblr dataset. Additionally, all images with a resolution lower than 300 x 300 pixels were deleted from both datasets, as these were typically icons or of insufficient quality for analysis purposes. Following these cleaning procedures, the corporate dataset was refined to a total of 1723 images for analysis. Similarly, Tumblr dataset resulted in a total of 1830 images

4. Results

This section presents the findings from the analysis of color across three dimensions: syntax, semantics, and pragmatics. The syntax analysis focuses on the patterns of color usage. The semantic analysis discusses the syntactical analysis's outcomes and qualitatively explores the meaning behind the color observations. The semantics section also contains a comparison between human and technology representation in the corporate and Tumblr datasets utilizing object detection. Finally, the pragmatics analysis examines the encoding and decoding processes of how color and object representation shape the reception and interpretation of visual messages.

Syntax color analysis

First, I ordered the images by color using the ImageSorter software to get a distant overview of the two different datasets. Here, I define syntax as the relationship between the images in the dataset. Here we can see the first general remarkable aspects.

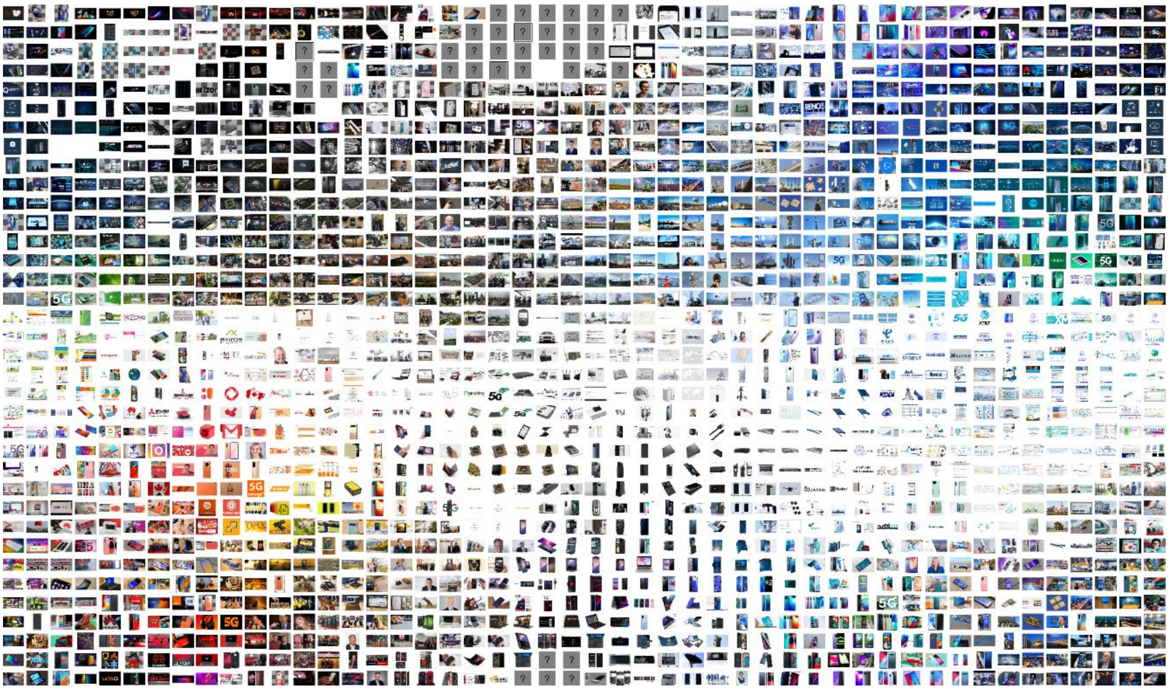

Figure 3: Corporate Dataset of 1723 Images Sorted by Color

Figure 3 depicts the corporate dataset as divided into two halves: a dark black and blue top and a light orange, white, and multicolored bottom. The white areas consist mainly of product images with a white background. I see almost no white images containing large texts. The blue and purple takes up a lot of space in the overview, but there appears to be no consistent pattern in the content.

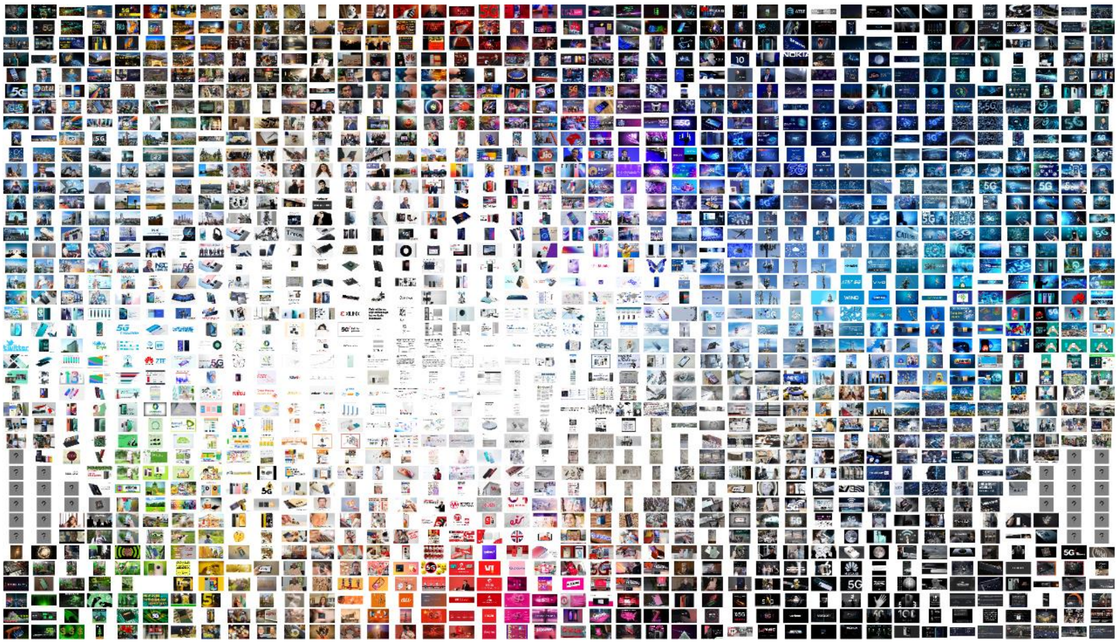

Figure 4: Tumblr Dataset of 1830 Images Sorted by Color

The Tumblr dataset shown in Figure 4 contains a small white area in the middle, but on average, seems relatively dark on the boarders of the collage. Some bright green, orange, red, purple, and blue colors are catching the eye. On the higher right side, the blue glow seems to contain many images with the term '5G' written over the span of the whole image. The white area seems to consist out of product images with a white background, and out of images containing texts. The remaining color areas are less identifiably patterned. After the first scan, the Tumblr set seems to contain a larger number of darker images than the corporate set. The Tumblr set also seems to have brighter colors and fewer white spaces than the corporate set.

<u>Color clustering</u>

Having Saint-Martin's coloreme theory reshaped into a theory that considers the relationship between pixels, the color of every pixel in an image was determined. A K-Means clustering algorithm clustered the pixels into five HEX color clusters. For computational efficiency, $K = 5$ was chosen. The color cluster containing the most pixels was selected for analysis and visualisation. Therefore, it is important to keep in mind that this analysis focuses only on the most prominent color in each image and does not account for all colors in the image. Every most common color was split up into four color characteristics: luminance, hue, saturation, and value. All characteristics have been sorted from lowest to highest value dependent by the type of characteristic. In figures 5 and 6, the luminance of the Tumblr and corporate datasets are visualized into a sorted color rectangle. Color luminance represents the measure of brightness of a color. It is a combination of intensity and lightness and quantifies how much light a color emits or reflects. It is calculated by using the formula $Y = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B$, with RGB being the red, green, and blue values (Yang et al., 2007). The output is a value between 0 and 255 with 0 representing complete darkness, and 255 representing the maximum possible brightness. This is typically white. Luminance affects how colors are perceived and how visual information is processed (Gonzalez & Woods, 2018).

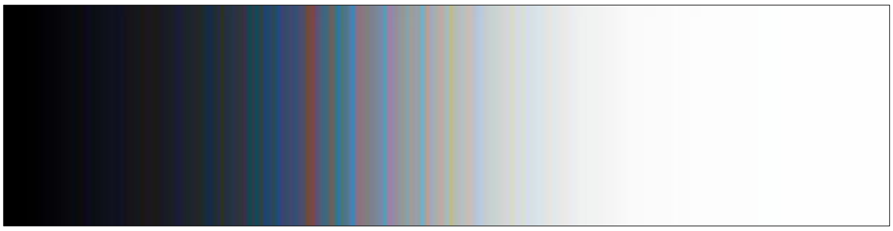

Figure 5: Corporate, Sorted Luminance of Most Common Color per Image

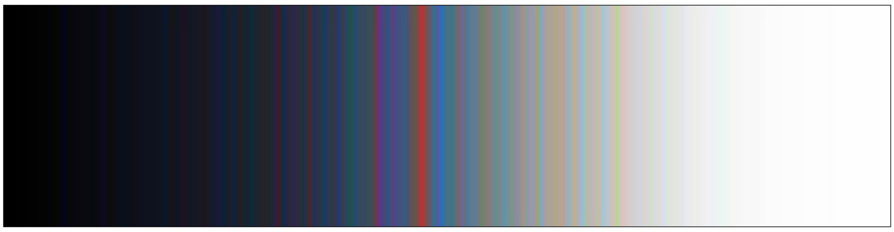

Figure 6: Tumblr, Sorted Luminance of Most Common Color per Image

When performing distant reading on the two luminance visualizations of the corporate dataset and the Tumblr dataset, a difference can be seen in the brighter luminance of the corporate dataset. This is in line with the first observations of the color-sorted datasets by ImageSorter in figures 3 and 4. The corporate dataset's color luminance starts to become bright almost halfway down the rectangle, and the Tumblr rectangle reaches its brightest form after roughly three quarters of the rectangle. The images seem to have the same amount of very low color luminance values (black and dark gray). Additionally, a bright red bar stands out in the Tumblr dataset. When consulting Figure 4, which contains all Tumblr images sorted by ImageSorter, the images that represent the red area can be seen at the top and bottom of the data collection.

In figures 7 and 8, the corporate and Tumblr datasets are sorted by color based on hue. Hue is the most readily detected difference between two isolated colors and is often described in terms of common color names like red, yellow, green, blue, etc. (Evans, 1972). Values within the ratio from 0 to 1 represent an ascending order of colors. From left to right, this is red, yellow, green, cyan, blue, magenta, and back to deep red. Initially, color hue was represented in degrees with a ratio of 0 to 360 degrees. Here, degrees were normalized to a ratio between 0 and 1. For example, values between 0.5 and 0.66 represent cyan/blue on the original color wheel (Gonzalez & Woods, 2018). The white spaces within the rectangles are most likely explained by a hue similar to its neighboring color, but with a very high HSV value, representing a color very close to white with a colored undertone. This also goes the other way around, representing black bars as having similar color hues compared to their neighbors but with a very low HSV value that results in a color close to black. For example, the hex color #020305 is perceived as black with a very low HSV value of 0.02. Its color hue is 0.61, representing a blue undertone; therefore, it is visualized in between the blue color hue's.

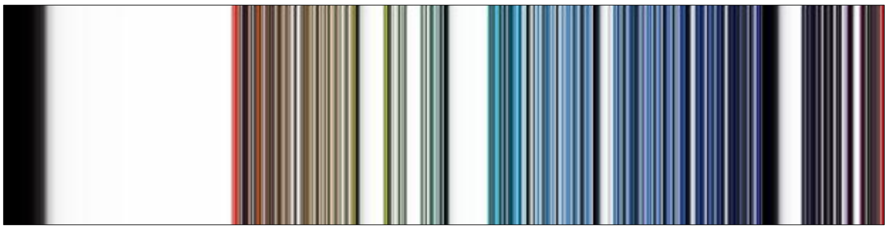

Figure 7: Corporate, Sorted Hue of Most Common Color per Image

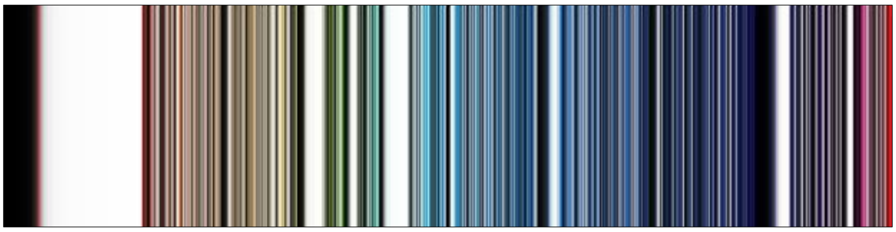

Figure 8: Tumblr, Sorted Hue of Most Common Color per Image

When performing distant reading on both hue visualizations, the Tumblr dataset is perceived as more diverse in terms of hue. As a result, it covers a wider variety of colors across the spectrum. Whether it truly is more colorful than the corporate dataset depends on its saturation and value. The corporate dataset has a narrower range of hues and more colors with a low value, leading to more white spaces and a less colorful appearance. The Tumblr dataset contains a substantially large, blue-toned area. For the corporate dataset, blue-toned colors also seem to be the most used in the images.

Saturation is the third color characteristic that is visualized. The amount of hue that can be seen is known as saturation. It is helpful to think of color saturation as color concentration. As the saturation increases, the mixture contains less white light and the perceived color becomes more visible and intense (Evans, 1972). The color saturation has a range between 0 and 1. The lower the saturation, the duller and grayer the colors can seem.

Figure 9: Corporate, Sorted Saturation of Most Common Color per Image

Figure 10: Tumblr, Sorted Saturation of Most Common Color per Image

The Tumblr dataset (Figure 10) appears to be more highly saturated than the corporate dataset (Figure 9). The darker appearance suggests that the colors in the Tumblr dataset have a lower brightness on average, implying the use of more muted or deeper colors. The corporate dataset appears to contain more colors with a lower saturation than the Tumblr dataset. This could indicate lighter and less saturated colors, resulting in a lighter overall appearance. The intense bright and dark colors on the right side of both rectangles indicate the presence of highly saturated and dark colors. The Tumblr dataset is richer in these highly saturated colors than the corporate dataset.

Color value is the last analyzed color characteristic. Colors can range from being too dim to being too bright to be seen. Colors with a high value are light and appear closer to white. Colors with a low value are dark and appear closer to black (Evans, 1972). In this case, both datasets look quite similar, except for the right side of the rectangles that visualize the corporate dataset (Figure 11) and the Tumblr dataset (Figure 12). It has become clear that the corporate dataset contains a lot of light images. The Tumblr dataset shows a slight difference, with colors appearing slightly darker and having a higher overall value compared to the corporate dataset.

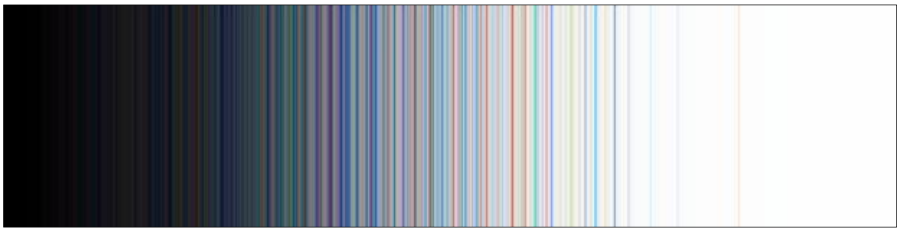

Figure 11: Corporate, Sorted Value of Most Common Color per Image

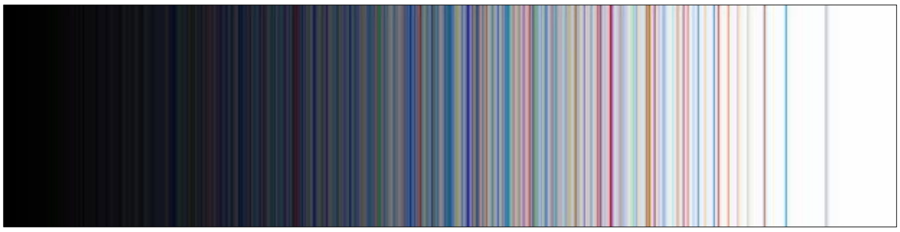

Figure 12: Tumblr, Sorted Value of Most Common Color per Image

For the color characteristics, descriptive statistics were calculated so the observations could be checked for significance. The descriptive statistics of the corporate dataset contain values between the minimum and maximum reachable values for each color characteristic: luminance, hue, saturation, and value. Table 1 illustrates this. The same goes for the color characteristics of the Tumblr dataset. Table 2 presents the descriptive statistics of the Tumblr dataset.

Table 1: Descriptive Statistics, Corporate

	N	Minimum	Maximum	Mean	Std. Deviation
Luminance	1670	,00000000000	254,00000000	151,93203114	97,209568057
HUE	1670	,00000000000	,99891774892	,35381281150	,29705195482
Saturation	1670	,00000000000	1,0000000000	,23815475865	,31061266193
Value	1670	,00000000000	,99607843137	,65079253258	,36679599931
Valid N (listwise)	1670				

Table 2: Descriptive Statistics, Tumblr

	N	Minimum	Maximum	Mean	Std. Deviation
Luminance	1596	,00000000000	254,00000000	122,67627381	93,579468114
HUE	1596	,00000000000	,99913194444	,40730378141	,29089857578
Saturation	1596	,00000000000	1,0000000000	,32506304895	,32899284009
Value	1596	,00000000000	,99607843137	,55675463168	,36066639601
Valid N (listwise)	1596				

When comparing the luminance means, the Tumblr dataset has a lower luminance mean than the corporate dataset. On a scale from 0 to 255, the images posted on Tumblr have a luminance mean of 122.68. The corporate dataset has a luminance mean of 151.93. This implies that on average, the Tumblr dataset contains darker colors that emit or reflect less light than the colors of the corporate dataset. An independent samples test was conducted (see Table 3) to test if the datasets are significantly different from each other based on luminance, hue, saturation, and value. A two-sided t-test revealed a significant difference ($t = -8{,}756, df = 3264, p < 0.001$) in luminance. The Tumblr dataset has a significantly lower luminance mean compared to the corporate dataset.

In comparing color hue between datasets, a two-sided t-test confirmed a significant difference ($t = 5.196, df = 3264, p < 0.001$). The hue mean for Tumblr is 0.407, and for the corporate dataset 0.354. The Tumblr dataset has a significantly higher hue mean compared to the corporate dataset. On average, the color hues of both the Tumblr and corporate dataset lay in the green/cyan color hue domain (±0.333 for green, up to ±0.5 for cyan), with the Tumblr dataset leaning more toward the cyan domain, and the corporate dataset leaning more toward the green domain. Whether this is an indication that the descriptive statistics supports the observation that the colors in the Tumblr dataset are more pronounced in terms of their hue compared to the corporate dataset, is hard to say. This will be clarified and further interpreted in the color semantics section.

For color saturation, a two-sided t-test indicated a significant difference ($t = 7.765, df = 3264, p < 0.001$). The corporate dataset has a significantly lower average saturation with a value of 0.238, than the Tumblr dataset with a saturation mean of 0.325. This indicates that the colors in the Tumblr dataset are more vivid and intense compared to the corporate dataset, which contains a higher number of muted and washed-out colors.

When it comes to color value, a two-sided t-test revealed a significant difference ($t = -7.384, df = 3264, p < 0.001$). The corporate dataset has a mean color value of 0.651, which is significantly higher than the mean color value of 0.557 observed in the Tumblr dataset. This implies that the corporate dataset on average contains brighter and lighter colors than the Tumblr dataset.

Table 3: Independent Samples Test, Color Analysis

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p			Lower	Upper
Luminance	Equal variances assumed	11,096	<,001	-8,756	3264	<,001	<,001	-29,25575733	3,3413549910	-35,80712215	-22,70439251
	Equal variances not assumed			-8,763	3263,827	<,001	<,001	-29,25575733	3,3384754587	-35,80147640	-22,71003825
HUE	Equal variances assumed	10,790	,001	5,196	3264	<,001	<,001	,05349096991	,01029368793	,03330822814	,07367371169
	Equal variances not assumed			5,199	3262,057	<,001	<,001	,05349096991	,01028880622	,03331779520	,07366414462
Saturation	Equal variances assumed	23,489	<,001	7,765	3264	<,001	<,001	,08690829030	,01119210964	,06496402111	,10885255949
	Equal variances not assumed			7,755	3229,948	<,001	<,001	,08690829030	,01120668612	,06493535520	,10888122539
Value	Equal variances assumed	,186	,666	-7,384	3264	<,001	<,001	-,0940379009	,01273539214	-,1190080703	-,0690677315
	Equal variances not assumed			-7,387	3261,353	<,001	<,001	-,0940379009	,01273052920	-,1189985431	-,0690772587

Semantic color analysis

This section delves into the color semantic analysis of the datasets, exploring the meanings and symbolisms of the color characteristics in corporate promotions and Tumblr blog posts. Building on the syntax analysis, this part aims to uncover underlaying narratives by combining the differences in luminance, hues, saturations, and values and connecting the results to color symbolics. It is important to keep in mind that the results of the syntax analysis focus only on the most dominant color per image.

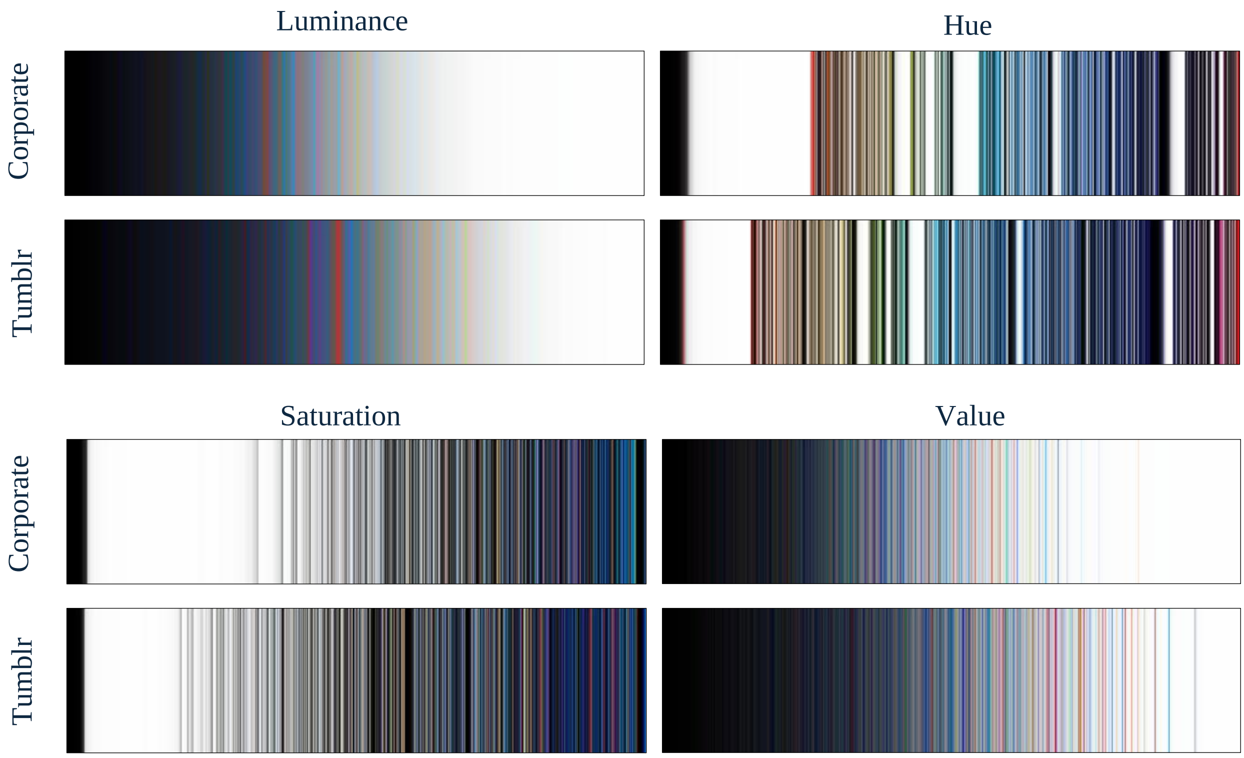

Figure 13: Color Visualisations of Dataset Sorted by Color Characteristic

The syntactical color analysis showed that the corporate dataset has a significantly higher luminance and color value, lower saturation, and a narrower range of hues, resulting in a brighter and more uniform appearance. The Tumblr dataset has a significantly wider range of hues, higher saturation, and lower luminance and color value, leading to a visually darker and more diverse color palette. I will break down the categories into a semantic interpretation of the color characteristics that describe both datasets.

Luminance and HSV value

Although luminance and value are two distinct properties in the perception of light, they both are indicators of color brightness. While luminance measures how much light is reflected, value represents the intensity and brightness of a color. The semantic interpretation merges the two characteristics into 'brightness' due to the lack of a literary framework that distinguishes between luminance and value in terms of brightness.

On a scale from 0 to 255, the Tumblr dataset has an average luminance of 122.68. The corporate dataset has a score of 151.93. On a scale from 0 to 1 for color value, the Tumblr dataset averages 0.557, and the corporate dataset averages 0.651. A two-sided t-test revealed a significant difference between the luminance in the corporate dataset and the Tumblr dataset. The two-sided t-test for color value proved the same significant difference. Based on luminance and value, corporate images are on average lighter, emitting or reflecting more light and indicating more bright colors compared to corporate images. From a distant view (see Figure 13 'luminance' and 'value'), the use of colors that emit a very low amount of light and have a very low brightness appears to be equal for both datasets. The middle section of the Tumblr dataset contains some darker colors than the corporate dataset, as the white space in the corporate rectangle arises earlier than in the color rectangle of the Tumblr dataset.

Research by Labrecque and Milne (2012) indicates that color brightness has an impact on emotional responses, even more than color hue. Relevant for the significantly brighter corporate dataset is that the results stated that bright colors induce a calming effect and lessen the arousing impact of hues. Colors with a higher brightness are also associated with decreased levels of dominance. For the significantly less bright Tumblr dataset, colors with a lower brightness were rated as higher on ruggedness, a characteristic that evokes a feeling of being big and strong (Labrecque & Milne, 2012). While brighter colors promote calmness, less bright images evoke ruggedness.

<u>Hue</u>

The hue analysis for the Tumblr dataset pointed out an average color hue of 0.407, and for the corporate dataset, an average of 0.354. A two-sided t-test confirmed a significant difference in the color hue. The Tumblr dataset leans on average towards a cyan color space. The corporate dataset leans toward a green color space. A problem that arises is that the mean is not a sufficient reflection of the true colors in the dataset and could indicate several outcomes. The hue's mean does not accurately reflect the color that emerges when all hues are combined. For the color hue, the mean is an interpretation of color diversity. You can consider it a push-pull mechanism on the color spectrum. As color hue is arranged from 0 to 1, with values sorted in the same order as the colors of the rainbow, a mean close to 0.5 could show an equal and balanced representation of colors in the dataset. However, it could also indicate a high presence of red, which is low in value, combined with a high presence of purple, which is high in value. Therefore, I will utilize a distant reading of the hue-color rectangles depicted in Figure 13.

The distant reading of the corporate and Tumblr datasets conveys a wide range of colors. According to research on psychological effects by Lebrecque and Milne (2012), each of these colors belongs to an associated emotion. From left to right on the color hue spectrum, red is linked to excitement, arousal, and stimulation. The color enhances likability and draws attention. Orange is known for being arousing and exciting. Yellow elicits feelings of optimism, extraversion, and friendliness. Green is associated with nature and evokes feelings of security and connection with the outdoors. Blue stands for competence, intelligence, communication, trust, efficiency, duty, and logic. The relationship between competence and blue is positive. Dark purple is associated with sophistication. Pink is associated with sincerity and sophistication. Black signifies sophistication, glamour, power, stateliness, and dignity. White stands for sincerity, purity, cleanness, simplicity, hygiene, clarity, and peace. There is a positive relationship between sincerity and whiteness.

According to Figure 13, the corporate dataset differs in the use of less diverse color shades and the extensive appearance of white. Tumblr exhibits diversity in each color of the spectrum. Compared to the corporate dataset, the Tumblr color hue stands out in the use of bright red, green, and black. According to Labrecque and Milne’s research on color associations, the corporate dataset has more associations with cleanness and clarity, represented by white. The colors where the Tumblr dataset contrasts in evoke associations with feelings of excitement, arousal, stimulation, security, sophistication, power, and dignity.

Saturation

The mean saturation for the Tumblr dataset is 0.325, compared to 0.238 for the corporate dataset. A two-sided t-test indicated a significant difference in saturation, with Tumblr images containing more intensely saturated colors than the corporate dataset (see Figure 13 ‘saturation’). Labrecque and Milne conclude that according to psychological effects on color, saturation has a positive effect on arousal, ruggedness, and excitement. Colors that are highly saturated induce feelings of dominance. Tumblr’s average saturation is, although still low, a bit higher than the average saturation of the complete dataset. Interpreted by the results of Labrecque and Milne, this indicates a slightly higher effect on arousal, ruggedness, and excitement in the Tumblr dataset. In contrast, corporate images exhibit lower saturation, suggesting a slight preference for less dominance, arousal, ruggedness, and excitement.

Semantic object analysis

In this results section, the differences between the corporate and Tumblr datasets are explored by focusing on the representation of human and technology-related objects. The Ultralytics YOLOv8 pretrained model was used to detect objects within the images from both datasets. Once an object is identified and labeled as, for example, a person, it enters the semantic domain. The label now carries an interpretive meaning.

After running the YOLOv8 model on the corporate and Tumblr datasets, the objects detected were summed up. Table 4 prints the results of the corporate dataset. The results of the Tumblr dataset are printed in Table 5.

Table 4: Corporate Object Detection Results

Object	Count	Object	Count	Object	Count
person	1211	potted_plant	19	vase	5
cell_phone	461	umbrella	18	backpack	5
laptop	116	mouse	18	tennis_racket	4
tie	109	bird	17	skateboard	3
car	101	dining_table	16	sports_ball	3
tv	83	bowl	15	orange	3
book	57	kite	13	couch	3
remote	55	boat	13	dog	3
traffic_light	49	bu	11	baseball_bat	2
chair	49	frisbee	10	cake	2
train	42	microwave	8	bus	2
airplane	42	surfboard	8	bed	2
suitcase	41	apple	7	teddy_bear	2
truck	31	motorcycle	7	donut	2
refrigerator	28	handbag	7	horse	2
cup	26	toilet	6	wine_glas	2
stop_sign	26	parking_meter	6	toothbrush	1
clock	23	oven	6	banana	1
keyboard	21	bench	5		
bottle	20	scissor	5		

Table 5: Tumblr Object Detection Results

Object	Count	Object	Count	Object	Count
person	1325	train	16	cake	4
cell_phone	338	refrigerator	15	bicycle	4
tie	129	mouse	14	backpack	4
car	77	scissor	13	snowboard	3
remote	67	vase	13	knife	3
book	64	truck	13	cat	3
airplane	56	keyboard	12	banana	3
clock	54	surfboard	11	baseball_bat	3
tv	50	microwave	10	sink	3
traffic_light	49	bu	10	dog	3
chair	45	horse	9	wine_glas	2
laptop	41	bowl	8	scissors	2
cup	32	toilet	8	apple	2
umbrella	32	tennis_racket	7	teddy_bear	2
potted_plant	31	bed	7	bench	2
stop_sign	27	couch	7	baseball_glove	1
kite	26	orange	7	broccoli	1
suitcase	23	handbag	6	ski	1
bottle	21	motorcycle	6	toothbrush	1
bird	21	donut	5	fork	1
frisbee	20	parking_meter	5	giraffe	1
dining_table	18	oven	4	sheep	1
boat	17	hot_dog	4	spoon	1
sports_ball	16	skateboard	4	fire_hydrant	1

After looking through the results in tables 4 and 5, some individual images from the labeled dataset were scanned to interpret the outcomes in the table. To define the word ‘technology’ for this analysis, I take into account all electronic devices that have a screen. Objects that qualify as this are phones, laptops, TVs, etc. Some outstanding results were the high number of remotes, traffic lights, kites, frisbees, and refrigerators. Upon closer inspection, it became clear that the model occasionally misclassified some objects. However, these misclassifications were consistent; for example, a detected misclassified refrigerator was always a cell phone. Therefore, these mislabeled objects were also classified as ‘technology’ for this analysis. Figure 14 shows examples of consistently mislabeled objects and explains why these do or do not qualify as ‘technology’. After evaluating individual cases of the objects labeled as remotes, refrigerators, traffic lights, kites, and frisbees, the decision was made to include the labels remotes and refrigerators as ‘technology’. Of the detected images containing ‘refrigerators’ and ‘remotes’ that were evaluated, all these objects were cell phones that were mislabeled.

Figure 14: Consistent Mislabeled Objects

Labeled traffic lights, kites, and frisbees were mislabeled as non-relevant objects for this analysis, thus not included in the technology count. Examples of these misclassifications are portrayed in Figure 14. Some objects relevant for this study were not labeled at all. Currently, the model is unable to detect objects such as 5G towers, telecom antennas, digital art, and memes. Although it would have been beneficial for the research if the model was able to do this, the distinction between humans and technology has been chosen because the model is skilled at correctly labeling these objects.

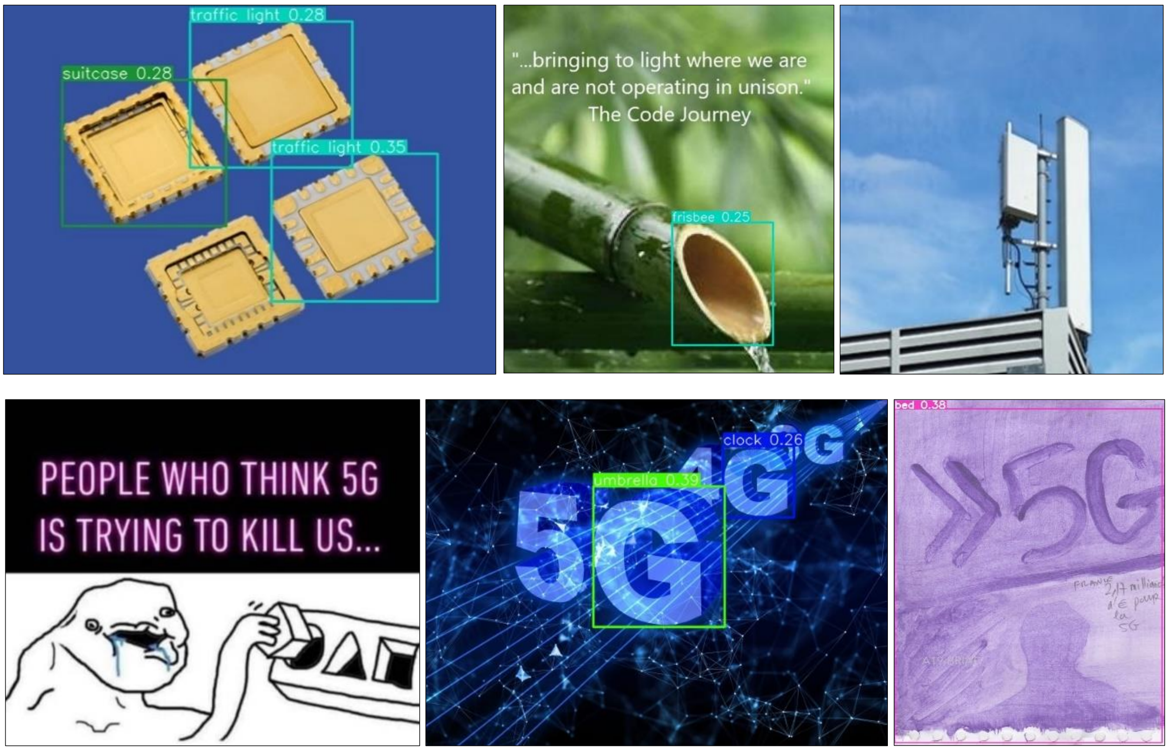

Figure 15: Mislabeled and Unlabeled Objects Excluded from the Analysis

Figure 15 shows multiple examples of consistently correctly labeled objects in images. The main findings are that the model is very suitable for detecting humans, phones, laptops, and TVs as seen in Figure 16. In this analysis, the categories of cell phones, laptops, TV's, remotes, and refrigerators were summed up under the collective noun 'technology'. The category 'keyboard' was excluded from the 'technology' category since the phones and laptops that the keyboards belonged to already were correctly labeled. Including the keyboard counts would result in duplicates in the technology category. The label 'person' is left as is and suitable for this analysis without any adaptations.

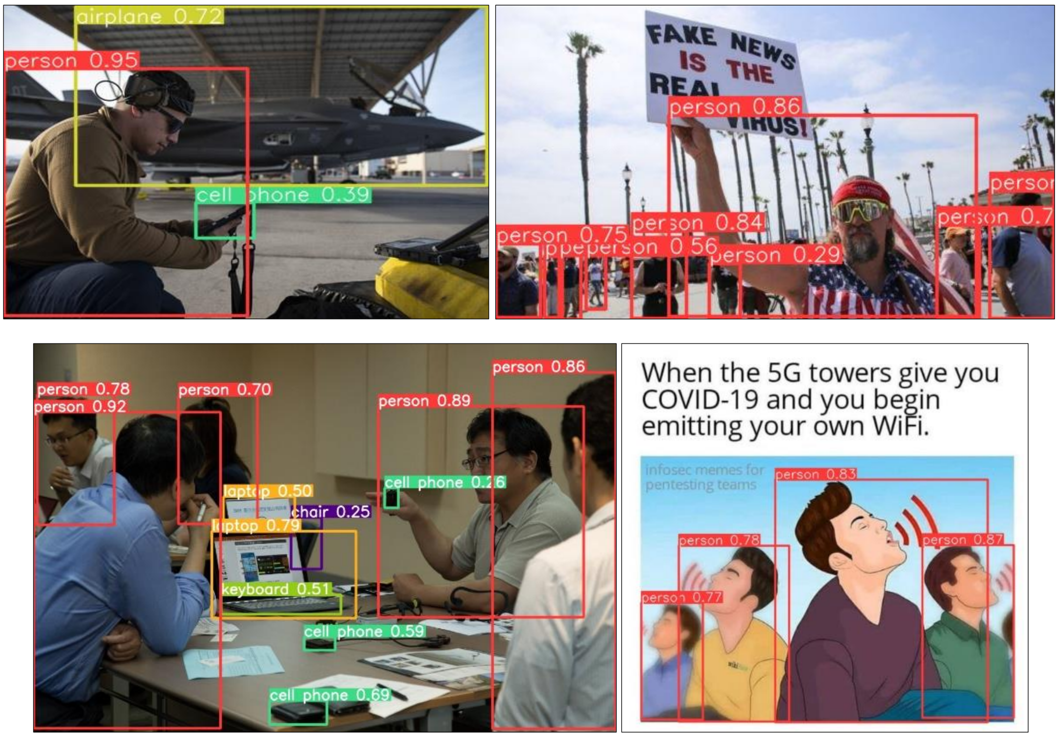

Figure 16: Correctly Labeled Images

After selecting the labeled object categories and gathering them into the 'technology' group, the Tumblr dataset can be compared with the corporate dataset. Tables 6 and 7 represent the technological object detections in the corporate and Tumblr dataset.

Table 6: Corporate Object Detection Results

Object	Count
Cell phone	338
Laptop	41
Tv	50
Remote	67
Refrigerator	15
Sum	511

Table 7: Tumblr Object Detection Results

Object	Count
Cell phone	461
Laptop	116
Tv	83
Remote	55
Refrigerator	28
Sum	743

Figure 17 shows that the corporate dataset counts 1325 humans and 511 technological objects in 1712 images. The Tumblr dataset counts 1211 humans and 743 technological objects in 1597 images.

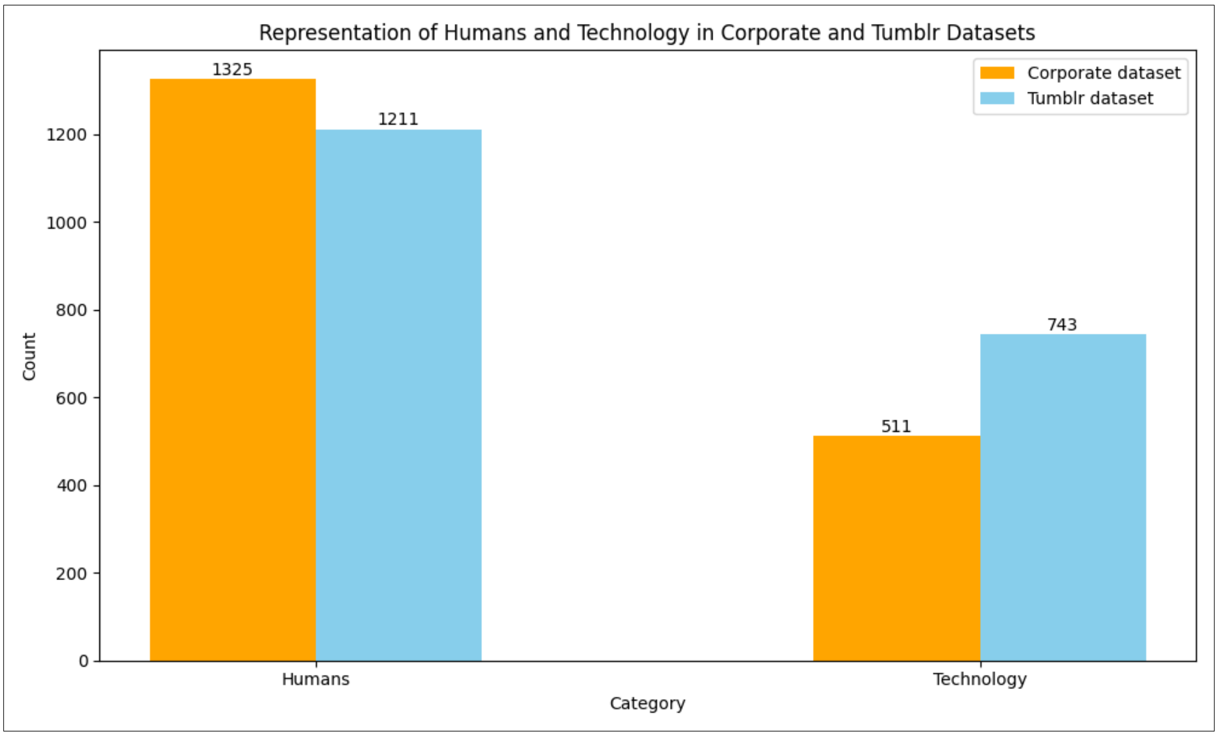

Figure 17: Representation of Humans and Technology in Corporate and Tumblr Datasets

To analyze if there are any significant differences between the two datasets, a hypothesis test was performed for the proportions of humans and technological objects between the corporate and Tumblr datasets. The total number of objects in the corporate dataset is 2853. The total number of objects in the Tumblr dataset is 2845. $H0$ states that there is no difference in the proportions of humans and technological objects between the corporate and Tumblr dataset. $H1$ states that there is a significant difference in the proportions of humans and technological objects between the corporate and Tumblr dataset. For the technological objects $(Z = 7.593, p < 0.001)$, $H0$ was rejected meaning that a significant difference was found between the two datasets. However, $H0$ was not rejected for the proportions of humans detected meaning that there was no significant difference found here in both datasets $(Z = -0.958, p = 0.338)$.

The Tumblr dataset contains significantly more technological objects than the corporate dataset. For the analysis of detected humans in the images, the corporate dataset has a higher presence. However, this difference is not significant.

Pragmatic analysis

Building upon the syntactic and semantic results, this pragmatic analysis will dive into the contextual outcomes of the imagery portraying 5G technology. This analysis integrates Stuart Hall's Encoding and Decoding model to understand the broader social and cultural implications of the images. According to Hall, media messages are encoded by producers and decoded by audiences. This potentially leads to diverse interpretations based on social and cultural contexts. In this analysis, the corporate dataset is referred to as the encoding entity, and the Tumblr dataset is referred to as the decoding entity.

This analysis lacks the incorporation of metadata and additional analysis that would be necessary to validate pragmatic interpretations. Therefore, the current conclusions are based solely on the syntactic and semantic analyses and assumptions about the motives of corporate messaging about 5G technology.

Encoder: corporate content

In the context of visual messaging about 5G technology, the companies that profit and benefit from 5G technology are seen as the encoding entity as they post images that provide information and help sell their products. These images are encoded with ideas by the producers who make them. In this case, the companies put certain ideas into their visual messages. They hope the audience takes away the message as intended, also known as the preferred reading. It is hypothesized that the encoding entity aims to establish a positive association with their visual messages. The companies make a profit selling 5G products and using their images for marketing purposes. The same motivations appear to be recognizable in the syntax and semantic analysis patterns:

The average higher brightness and lower saturation of the images in the corporate dataset was found to be associated with calmness and decreased dominance. Used color hues were light blue, yellow, orange, and white. Linking to competence, intelligence, communication, security, excitedness, optimism, cleanliness, and clarity. These characteristics could implicate a sense of stability, trustworthiness, and reliability in 5G technologies. Corporate images tend to include humans in their representation of objects, though not significantly more than Tumblr images. Scanning through the dataset leads to observations that highlight the inclusion of humans in a professional and controlled setting, assumingly emphasizing the practical benefits of 5G technology. Together, the use of brightness, saturation, colors, and objects could hint at a preferred reading of user-friendliness.

Decoder: Tumblr user-generated content

According to Hall's theory, media messages are decoded by audiences. This context views Tumblr user-generated content as the decoding entity. Tumblr users interpret and react to messages they've seen in the media. In this case, the corporate-encoded messages are hypothesized as influences on the opinions of the Tumblr audience, to which the Tumblr users produce content that reflects their own perspectives and emotional responses. According to syntax and semantic analysis, the following overall message can be interpreted from the Tumblr images:

The average lower brightness and higher saturation in the Tumblr dataset are associated with ruggedness, strength, and dominance. Some of the more used color hues were dark blue, yellow, red, green, and black. Research by Lebrecque and Milne found that these colors were linked to a feeling of sophistication, intelligence, communication, trust, optimism, excitement, arousal, stimulation, security, and power. Overall, the darker tones and more diverse color palette could be interpreted as a dynamic and engaging perception of visual messaging. There is a difference between the expression of calmness and decreased dominance in the corporate dataset and excitement and decreased dominance in the Tumblr dataset. The Tumblr images contain significantly more technological objects compared to corporate images. This can be interpreted as a focus on the technological aspects of 5G technology, highlighting user engagement with the technology itself rather than user-friendliness.

Pragmatic Implications

The encoding and decoding model categorizes the audience’s interpretation into three types: a dominant position, negotiated position, or oppositional position. When dominant reading is applicable, the audience fully accepts the encoded message as intended by the producers. A negotiated reading occurs when the audience acknowledges the encoded message but adapts it to fit their own experience and context. For oppositional reading the audience understands the encoded message but rejects it, interpreting it in a contrary manner (Hall, 1973).

Based on the hypothesized differing roles of the corporate and user-generated groups, where the corporate content is seen as the encoded messaging and the Tumblr content as the decoding of the corporate messaging, the overall decoded message by Tumblr users appears to fall into the category of a negotiated reading. The users partially accept the positive associations encoded by the corporate content. Upon initiating a cautious attempt to interpret the negotiated position, differences between the color characteristics in the datasets could be interpreted as visual messaging emphasizing the diverse character of the 5G discourse, technological engagement, and encouragement to contribute to the conversation. This negotiated reading highlights the dynamic interaction between corporate messaging and audience reception, influenced by social and cultural contexts.

5. Discussion

The findings of this study shed light on the visual semiotics of corporate and user-generated 5G imagery while also serving as explorative research. Content posted on social media can heavily influence and shape societal beliefs and actions. Therefore, it is important to understand the process of interpretation and exchange of information. With the increasing use of visual images on the internet, this study advocates for a data-scientific approach to visual semiotics. Using mixed methods, the differences between the visual semiotics of 5G technology imagery in corporate-produced content and user-generated content were researched. Following the foundations of semiotics created by Charles Morris, the research method was split up into three divisions building upon each other. First, syntax analysis was conducted. Second, the results of the syntax analysis were interpreted in a semantic analysis. Finally, for a pragmatic analysis, the results of the first two analyses were used. To answer the research question "How do the visual semiotics of 5G network imagery differ between user-generated content and corporate-produced content?", the results imply that the visual semiotics differ because of the following differentiating elements: color palette, emotional and psychological impact, representation of technological objects, and pragmatic narrative.

A difference in color palette and emotional and psychological impact was found after the syntax color analysis and successive semantic analyses. The syntax analysis showed that the corporate dataset has a significantly higher luminance and color value, significantly lower saturation, and a narrower range of hues compared to the Tumblr dataset. Semantic analysis uncovers that, based on research by Lebrecque and Milne, the color differences in value and saturation levels promote more calmness and lower dominance in relation to the Tumblr dataset. In relation to the Tumblr dataset, the color hues overlap greatly in occurrence but differ in the extent and diversity per color hue. Essentially, the corporate dataset contains all color hue categories, such as red, yellow, orange, green, and blue, but contains less diversity in the color tones of each category, such as light blues, bright reds, and all shades of green. Distant reading of the color rectangles revealed an overall difference in the higher occurrence of white as the main ‘color’ of a substantial number of images in the corporate dataset. Research on the psychological and emotional effects of color in marketing states that there is a positive relationship between whiteness and sincerity. White also evokes feelings of cleanliness, clarity, and peace.

The syntax color analysis of the Tumblr dataset showed that it has significantly lower luminance and color value, significantly higher saturation, and a more diverse color palette compared to the corporate dataset. The difference in value and saturation levels promotes a stronger relationship towards ruggedness, strength, and dominance compared to the corporate dataset (Labrecque & Milne, 2012). After distant reading of the color hue rectangles, the color hues differ in the occurrence of bright reds, greens, and blacks in relation to the corporate dataset. Semantic analysis uncovers that these most notable color differences in the Tumblr dataset are, according to marketing research, associated with feelings of excitement, arousal, stimulation, security, sophistication, power, and dignity. In relation to each other, the differences between the datasets amount to the corporate dataset portraying a brighter and more uniform appearance and the Tumblr dataset portraying a visually darker and more variated appearance.

Additional semantic object analysis uncovers a significant difference in the representation of more technological devices in the Tumblr dataset and a non-significant increase in the representation of humans in the corporate dataset. This could indicate a focus on the technological aspects of 5G technology in the Tumblr dataset, highlighting user engagement with the technology itself rather than hinted user-friendliness in the corporate images.

The findings mentioned above were used as input for pragmatic analysis. Stuart Hall's Encoding and Decoding model was used to gain an understanding of the informational interpretations of the Tumblr users about 5G technology messages provided by corporate entities. This pragmatic outcome finds clues that lean towards a differentiating narrative produced by corporate entities compared to Tumblr audiences. The syntactical and semantical comparison between encoding and decoding reveals that users partially accept the positive associations encoded in corporate content, but do not fully replicate the visual semiotics of the corporate dataset. Hence, the differences in color palette and technological objects. In terms of the Encoding and Decoding Theory, this is defined as a negotiated reading. Unfortunately, there is no method found that can validate these observations and assumed narratives. Therefore, this pragmatic analysis relies on hypothesized outcomes. The observation is based on the mentioned differences in color palette, psychological and emotional impact of color, and representation of technological objects. Every outcome mentioned has been analyzed based on the idea that it differs in relation to the other dataset. Therefore, no conclusions can be drawn about the isolated status of the visual semiotics in each dataset.

The three divisions of visual semiotics—*syntax, semantics, and pragmatics*—used in this research build on and rely on each other to form conclusions about the 'Unity of Visual Semiotics'. The Unity of Visual Semiotics lies in its approach to analyzing and interpreting the nuanced interactions between color and representation, offering insights into how visual communication shapes perceptions and meanings in both corporate and user-generated contexts.

5.1 Limitations and recommendations

Several limitations were encountered during the execution of this research. First, I want to acknowledge that semiotics is an immensely complicated and broad field of study. After careful consideration and multiple trials to convert existing semiotic theories to fit large datasets, I found that Charles Morris provided a foundation with which I saw possibilities to connect computational methods. This does not imply that other semiotic theories would not have been suitable for this type of research. I believe that more attempts would greatly benefit the data-science field. Delving into my methods, my syntax analysis only covers the biggest color cluster per image. As a result, many color outings are discarded before analysis. Using the most present color was an appropriate measurement, although it would be interesting to invest in a method that does not lose that much color information for every image in the dataset. Then, making decisions about which Tumblr hashtags to select for scraping the images was made difficult by Tumblr because of their policy that protects the spreading of misinformation. Hashtags such as '#5Gconspiracy' contained many deleted blogposts (see appendix A, Figure A1). Content moderation is an affordance of Tumblr that resulted in a dataset that was incomplete in the whole spectrum of opinions about 5G technology. A category of messages that expressed their concerns and disbeliefs about 5G was included, but to a limited extent. Apart from this, some corporate advertising got mixed into the Tumblr dataset because several telecom providers and news channels are active on Tumblr. I was not able to delete the corporate advertising from the Tumblr dataset. This may have led to some non-substantial noise in the dataset. Second, for the semantic interpretation of the syntax color I used marketing research that studied the psychological effects of color on consumers. Color semantics is a very broad field with a large scale of dimensions. Psychological effects differ in cultural and societal interpretations, or the symbolic meaning of color. I believe my choice for marketing research is fitting for the context of this research. However, it is not possible to make factual claims about the semantic meaning of color for each individual in every context. This area remains dependent on the scientific context.

Other method trials that, during the timespan of this research, contained too many limitations to follow up on are better translated in the form of potentials for future research. This research led to several potential directions. The process of this explorative research contained some trials and scrapped work, but at the same time, there were potential methods to explore further. In the trials to put together a method for the syntax analysis, I experimented with Gray Level Co-occurrence Matix feature extraction as a method to draw conclusions about the texture of an image. Thus far, there were no literary sources that used GLCM methods to generate meaning for visual analysis. The lack of a theoretical framework that could help me with semantic reasoning was too sparse, or even nonexistent, so I had to refrain from using this method for this project. For semantic analysis, it would have been evident to analyze all individual objects in the images of the dataset. Unfortunately, due to time constraints, there was no time to train the YOLOv8 classification model on the 5G technology datasets. The pre-trained model did not recognize crucial objects such as 5G towers. It would be interesting to train the model to be more accurate in classifying all objects and other types of technology in the images instead of only focusing on humans and cell phones, laptops, etc. This upgrade would be beneficial to semantic analysis. Another computer vision method that could be added to the semantic analysis is optical character recognition (OCR). Many images contain the text '5G', or even contain textual warnings about the technology. These textual aspects of the visual messages are not incorporated into the analysis at the moment, while providing much information about the meaning behind a visual message. Adding OCR to the semantic analysis, together with a classification model particularly trained on the types of images used for this research, would add a deeper layer for more detailed analysis. Finally, pragmatic analysis misses an aspect of interpretation validation. Performing text analysis on scraped metadata, together with corporate images and Tumblr blogs, could help resolve this problem and add a new dimension to the analysis. However, as literature critic Jonathan Culler states, metadata also provides context that frequently oversimplifies rather than enriches the discussion (Bal & Bryson, 1991). An interesting pragmatic analysis and discussion could arise from spending more research on this dilemma.

6. Conclusion

This research advocates for a data-scientific approach to visual semiotics. It compares images shared by two groups: corporate entities promoting the beneficial side of 5G networks and 5G-related content produced by users on Tumblr. The study divides visual semiotics into syntax, semantics, and pragmatics, allowing for algorithmic and computer vision methods while supporting qualitative interpretations. The research aims to understand how the visual semiotics of 5G technology imagery differ between corporate-produced content and user-generated content.

In summary, the visual semiotics of 5G network imagery on corporate platforms and Tumblr reflect differing priorities and communicative strategies. Corporate imagery is encoded to instill calmness and low dominance through a brighter and more uniform color palette that focuses on human elements. In contrast, Tumblr content is more diverse, vibrant, and technologically oriented, reflecting engagement in communication. These differences highlight the contrast between corporate attempts to encode and control their brand perception and user-generated content's role in decoding the corporate's preferred interpretation into creating dynamic narratives. This research marked an early stage in the exploration of finding a suitable framework and fitting computational methods that are able to interpret how representation generates meaning in large datasets of images. I aspire for this research to contribute to advancing visual semiotics into a data-scientific dimension.

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Appendix A – Supplementary material

Human-Computer Agreement

Tabel A1: Human-Computer Agreement Results

	Human-reviewed	Computer-reviewed	Accuracy
Person	47	49	0,96
Technology	30	27	0,9

Content Moderation on Tumblr

The initial posted material is covered with a message that states: “Nothing to see here. What you are looking for is not currently located at this address. Unless, of course, you were looking for this error page. In that case: congratulations, you've found it!”

Figure A1: Content Moderation Warning on Tumblr

Appendix B – OneDrive supplementary thesis files

Link: ADS Thesis Appendix B Files Mariëlle Kieskamp

Folder content

1. Datasets

- Corporate Images Dataset
- Tumblr Images Dataset

2. Python code used for computational methods

- Tumblr API scraping
- Color clustering
- Object detection
- Object word frequency

3. Output of computational methods

- Corporate color clustering CSV
- Tumblr color clustering CSV
- Corporate object detection output TXT
- Tumblr object detection output TXT
- Corporate object detection CSV
- Tumblr object detection CSV

4. Human-Computer Agreement object detection

5. Academic poster

Appendix C - Academic Poster Presented June 28, 2024

Full size academic poster is also available for viewing in the OneDrive folder

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Conflicting Wavelengths

Visual Semiotics Analysis on Encoding and Decoding in Corporate and User-Generated Imagery on 5G Technology

Applied Data Science Master's Thesis, Department of Information and Computing Science

Motivation and Research Question

During the COVID-19 pandemic, conspiracy theories linking 5G technology to the virus led to telecom towers being set on fire[1]. With the rise of visual images on social media, the image's role in spreading information and influencing societal perceptions has grown significantly[2]. A way to understand the exchange and interpretation of these images is through semiotics. Understanding the visual semiotics of 5G imagery can help address misinformation and shape public perceptions in an era where visual content heavily influences societal beliefs and actions. Traditional visual semiotics research has focused on individual images or small datasets. The high number of daily social media posts that appear online everyday call for a data-scientific approach analyzing large datasets. This study explores a method for a data-scientific approach to visual semiotics using the case study of visual messaging around 5G technology.

How do the visual semiotics of 5G technology imagery differ between corporate-produced and user-generated content?

Visual Semiotics: "How does representation generate meaning?"

An example: Lane markings

Syntax – structure of image

- Typically, white or yellow stripes, solid or dashed lines, usually on asphalt.

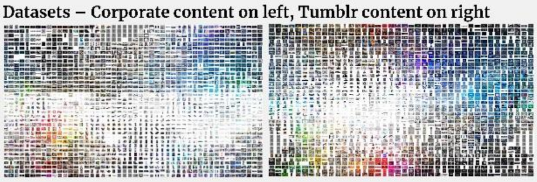
Semiotics – meanings associated with elements in image

- The lane markings indicate the rules of the road, regulating driver behavior.

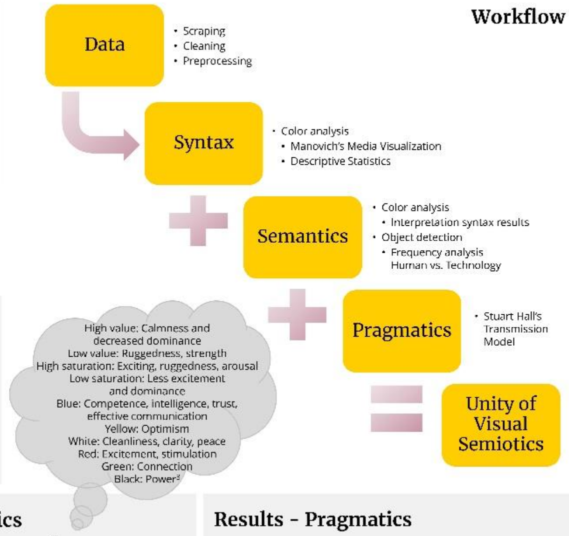
Pragmatics – context in influences interpretation

- Interpretation of the markings may vary per country. There is cultural context.

Datasets – Corporate content on left, Tumblr content on right

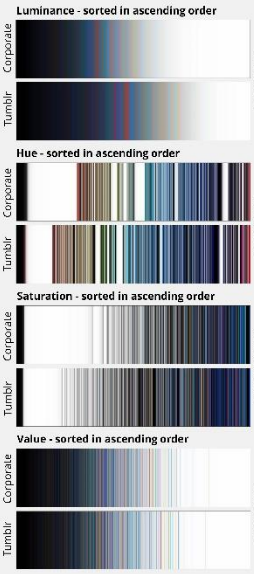


Workflow



Results - Syntax

Color analysis – Media Visualization and descriptive statistics



Average **luminance** of **corporate** dataset is **significantly higher** than Tumblr dataset.

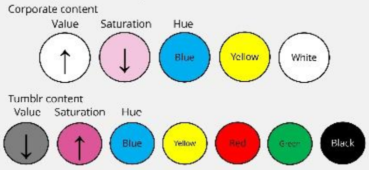
Average **hue** of **corporate** dataset is **significantly lower** than Tumblr dataset.

Average **saturation** of **corporate** dataset is **significantly lower** than Tumblr dataset.

Average **value** of **corporate** dataset is **significantly higher** than Tumblr dataset.

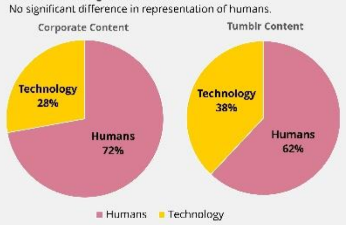
Results - Semantics

Interpretation syntax results



Object detection – Ratio Human vs. Technology

- **Corporate** content contains **significantly less technological objects** than Tumblr user-generated content.
- No significant difference in representation of humans.



Future work

- Texture analysis through feature extraction using Gray-Level Co-Occurrence Matrix (GLCM)
- Object classification after model training
- Optical Character Recognition (OCR)

Results - Pragmatics

Stuart Hall's Transmission Model: Media messages are encoded by producers and decoded by audiences. This potentially leads to diverse interpretations based on cultural contexts[4].

Encoder → Corporate generated content
Trust and calmness: Corporate images, with their controlled visual style, aim to reinforce trust. This encoding approach seeks to assure consumers of the safety, reliability, and benefits of 5G technology.

Decoder → User-generated content on Tumblr
Engagement and empowering: Tumblr images, with their diverse and expressive visual narratives, reflect a decoding that promotes active engagement. This response fosters a sense of community and co-creation, empowering users to contribute to the discourse around 5G technology.

Conclusion

- Visual semiotics of 5G network imagery on Tumblr and corporate platforms reflect **different priorities** and **communicative strategies**.
- **Corporate imagery** is designed to **gain trust, calmness, and professionalism** through a brighter and more uniform color palette, focusing on human elements.
- **Tumblr content** is **more diverse, vibrant, and technologically oriented**, reflecting personal expression and authenticity.
- These differences highlight a contrast between corporate attempts to control brand perception and user-generated content's role in creating diverse and dynamic narratives.

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