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ARTIFICIAL INTELLIGENCE APPLIED TO HATE SPEECH ANALYSIS: Trump and Biden During the Storming of the Capitol in Washington, D.C.

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ABSTRACT

In January 2021, during a rally in Washington, D.C., Donald Trump claimed electoral fraud and urged citizens to go to the Capitol. Hours later, dozens stormed the building, leaving four dead and 52 arrested. Afterwards, both Joe Biden and Trump released audiovisual messages. This study uses AI tools to qualitatively analyse those speeches via the ONEIA application. A quantitative analysis with OpenAI also assessed the videos' aesthetic treatment. Despite major content differences in the speeches, the audiovisual style showed high similarity, supported by statistical analysis of frame histograms..

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1. The assault on the Capitol: Trump and Biden

On 6 January 2021, a crowd stormed the United States Capitol. The occurrence of the event resulted in the interruption of the legislative session that would have certified Joe Biden's victory in the 2020 presidential election (Matthews, 2021). Hours earlier, protestors had attended Donald Trump's "Save America" rally in the public park known as the Ellipse. During his speech, Trump urged protesters to proceed to the Capitol and demonstrate fortitude (Simon, 2021): "We're going to walk to the Capitol, and we're going to cheer on our brave senators and congressmen and congresswomen. You have to demonstrate strength, and you must be strong" (BBC, 2021). Furthermore, Trump accused Biden of being an illegitimate president and instigated the fight to take back their country: "We will fight with all our might, and if we don't fight with all our might, we will lose our country" (BBC, 2021). On multiple occasions, the audience loudly voiced "fight for Trump!" in response to the US president's remarks (Fuchs, 2021; Simon, 2021).

Subsequently, a proportion of the protestors who had attended Trump's speech forced their way into the Capitol. In the course of the standoff at the gates, a law enforcement officer from Capitol Hill discharged a firearm at a protester, resulting in the latter's subsequent demise in a medical facility from the injuries sustained. Three other people died in medical emergencies, as well as police officer Brian D. Sicknick, from injuries sustained in the assault (Chace, 2021).

The protesters gained entry to the Capitol, where they proceeded to destroy furniture, steal official documents and take photographs, which they subsequently disseminated via social networks (Fuchs, 2021). It has been reported that a number of assailants advanced in the direction of several senators, including Mitt Romney, Nancy Pelosi and Vice President Mike Pence (BBC, 2021). As posited by several authors (Fuchs, 2021; Simon, 2021), the objective of this group was to utilise violence against certain senators with the aim of overturning the election result. During the course of the attack, Trump published a series of tweets offering counsel to the assailants to return home, characterising them as exemplary patriots, and concluding with the assertion, "Remember this forever!"

In the aftermath of the Capitol attack, Biden made a media appearance, asserting that American democracy was under unprecedented attack. He then proceeded to emphasise that the attacks on the Capitol do not represent authentic American values and beliefs and instead described the perpetrators as a small group of secessionist extremists. He then suggested that a president's words can incite violent acts, citing Trump as an example. Biden has called upon Trump to make an appearance in which he would defend the American Constitution and call for an end to the prevailing chaos. He then recalled that his administration would attempt to restore decency to American politics and society.

Two days after the attack, Trump released a video in which he clarified some of his positions on the Capitol attack (Durschlag, 2021). Trump stated that from the outset, his actions were in defence of the law, and that he had deployed the National Guard and the Federal Police to control the riot. He reiterated the notion that the United States is a nation founded on order and the rule of law, and he went on to accuse the protesters of failing to represent their country. Furthermore, he emphasised that individuals who had transgressed the law would be held accountable for their actions (Karni, 2021). Subsequently, he acknowledged the considerable intensity of the campaign but warned that tempers must be kept under control to ensure a peaceful transition of power. Furthermore, he emphasised his commitment to ensuring the integrity of the electoral process within the confines of the law, emphasising his dedication to maintaining fairness in the present and ensuring its continuity into the future (Durschlag, 2021). It has been posited by several authors (Mangan and Breuninger, 2021) that Trump's video could be part of a legal strategy to avoid a conviction for encouraging the assault on the Capitol. However, as posited by other authors (Sullivan and Bradner, 2021), Biden's video was intended to project an image of leadership and authority in the face of an unprecedented situation.

Despite the fact that numerous scholars have examined the content of Trump's and Biden's political messages in the aftermath of the Capitol Hill attack (see, for example, Chace, 2021; Fuchs, 2021; Simon, 2021), none have undertaken such an analysis by integrating the analysis of the speeches with the aesthetic elements of the image. The digital image has become an indispensable component of contemporary political communication. This phenomenon has already been observed in the 20th century through cinema and television, but the advent of the Internet and social networks has led to a paradigm shift in the value of the image. It is the contention of this paper's contributors that contemporary politics is characterised by an overarching emphasis on the visual and aesthetic dimensions that are an inherent component of the political landscape.

Although several studies (Galfione, 2014; Rai, 2017) have investigated aesthetic factors in current American politics and President Donald Trump (Leslie, 2019; Rasmussen, 2021), none have done so from a quantitative approach. The conversion of video content into quantifiable data facilitates analysis, thereby offering insights into the political messages conveyed by Biden and Trump. To date, studies that have focused on the analysis of the moving image have done so through the following areas: the types of shots, the elements of the frame, the type of photography, the colours used and the non-verbal language of the candidates. However, there is a paucity of research that analyses variations in the luminance of a video to determine its aesthetic significance.

2. Artificial Intelligence in Speech Analysis

A plethora of studies have been conducted on the utilisation of AI-based methodologies for text analysis (Gandhi et al., 2024). The majority of these solutions are driven by the necessity to moderate social networks (Badjatiya et al., 2017; Bunde, 2021; Gongane et al., 2022), particularly regarding the identification of hate speech and misinformation (Gongane et al., 2024; Khan at al., 2024; Modha et al., 2020). Discourses characterised by racism, homophobia, or discrimination on the basis of gender, religion, or social class have been particularly prevalent (Lee et al., 2022; Thiago et al., 2021). A significant proportion of these studies have concentrated on the detection of hate speech in particular contexts, including the ongoing Coronavirus pandemic (Chao et al., 2024), the war in Ukraine (Leekha et al., 2024), and the Rohingya refugee crisis (Palakodety et al., 2020). In many cases, studies have indicated that the discourses of political leaders are a contributing factor, as evidenced by the analyses of Bhattacharya et al. (2024) and Sharma et al. (2023).

These investigations have been addressed with different artificial intelligence (AI) technologies, the majority of which are encompassed in natural language processing (NLP) systems. One of the most widely used has been the BERT system, developed by Google AI Research (Alatawi et al.; 2021; Mozafari et al., 2020; Saleh et al., 2023). A significant number of studies have also been published that employ Chat GPT (Oliveira et al., 2023; Zhu et al., 2023) or the combination of other technologies (Fenza et al., 2024). Finally, multimodal discourse analysis in conjunction with aesthetics has been successfully carried out by some studies (Houssain & Muhammad, 2019; Kumar et al., 2024), although so far histogram analysis has not been used as the main source of data.

3. The Histogram as a Method for Representing Luminance

Image analysis using histograms is predicated, in its fundamental elements, on the composition of the digital image. It is an established fact that any image, whether photographic or audiovisual, is broken down into tiny units known as pixels (see Acharya and Ray, 2005; Angulo and Serra, 2005; Géraud et al., 2001; Russ, 2002). Each pixel is comprised of chrominance (colour) and luminance (light) information. Consequently, any digital image can be analysed based on the pixels that comprise it. One of the systems employed for their analysis is the histogram.

The histogram is defined as a graph with an abscissa and ordinate axis representing a variable distributed in frequencies (Behar Guitiérrez and Grima i Cintas, 2013). In the context of the luminance histogram, the x-axis is indicative of the range of tones. In the context of 8-bit images, it is possible to assign a total of 256 distinct values, ranging from black (0) to white (255). The following data sets represent the luminance values. The y-axis denotes the quantity of pixels comprising each tone, measured on a proportional scale (Glasbey, 1993). As it is proportional, the exact number of pixels for each tone is not shown, but rather an equivalent value. The maximum pixel value is set at 100, with a proportional value applied to the remaining pixels (Adam et al., 2006). Consequently, a histogram offers a concise representation of the tonal distribution within an image. An image that has been overexposed, or one that has been intentionally shot in high key, will be one whose maximum pixel values are located on the right side of the histogram. In addition, it will have a limited number of values on the vertical axis to the left. Conversely, in an underexposed image or one that is shot in low key, the opposite effect will occur. Consequently, if an image has been exposed in a balanced manner, the values will be distributed across the central area (Kurugollu et al., 2001).

However, it should be noted that each pixel is composed of information from three colour channels, and the brightness histogram does not represent them equally. This is due to the fact that it provides a sample of the perceived brightness. Given that the human eye does not possess equivalent sensitivity to all colours, the most relevant in this system is green. The weighted average indicates a result of 59% brightness for the green channel, 30% for red and 11% for blue (Flores et al., 2015). In this manner, the histogram is a visualisation of brightness in accordance with the perception thereof; that is to say, it provides a quantifiable means of representation relating to an inherent perceptual sensation.

A luminance histogram facilitates the analysis of each image in isolation. This phenomenon is particularly evident in the context of photographic analysis, yet it is equally applicable when examining audiovisual products. The division of a second into frames is dependent upon the capture system employed (NTSC, PAL, SECAM, or film). The number of frames per second can vary, with possible values including 24, 25, 29.97, among others. The extraction of a sample from a video facilitates the observation of light variations in each frame, as evidenced by the analysis of its luminance histogram. In a given shot, the movement of the constituent elements will be reflected in its histogram, as the luminance of its pixels varies accordingly. The analysis will provide direct information regarding the lighting conditions of the image, including whether the lighting is balanced, overly bright, or too dark.

It is evident that variations in the histogram can have a significant impact on the aesthetic qualities of an audiovisual work. A video characterised by numerous cuts, constant camera movements, lighting changes, or elements moving within the shot will exhibit greater variation in the luminance curves. In other words, each frame analysed will produce a curve that is significantly different from the previous or subsequent frames, as might be the case in a video clip. Conversely, in a single-shot video of a landscape, where there are no editing cuts and no internal movement, the opposite would occur. In the latter case, the histograms of each frame would be very similar. The extraction of luminance data from video footage facilitates the acquisition of substantial information, which can then be utilised for the purpose of conducting a statistical analysis of the aesthetic style of the video.

4. Objective

The primary objective of this study is to evaluate the image treatment and content of Trump's and Biden's political speeches following the storming of the Capitol, employing quantifiable data. Secondary objectives include the identification of any correlation between the images and a comparison of the different degrees of light exposure of each video. Furthermore, the correlation between the content of both speeches and their aesthetic treatment is also addressed.

5. Method and Sample

The present article employs a quantitative methodology based on the analysis of histogram data from both speeches, with a subsequent statistical output to assess means and significant differences (Atkinson, 2014; Fell et al., 2021). The OpenAI tool (Chat GPT, version 4) was utilised to analyse a random sample of twelve frames from each of the two speeches, those of Biden and Trump, following the Capitol assault (see Figure 1). This random selection is consistent with the parameters established in several recent studies (Koeing et al., 2012; Vafeiadis and Shen, 2021) and utilises footage with a resolution of 1920x1080 at 25 progressive frames per second, with a bitrate of 15,000 Kbps. The data from the AI application will provide a histogram of each of the selected frames, where the X-axis is the frequency and the Y-axis is the value of each pixel (0-255). The pixels that are closest to 0 are associated with dark values, where 0 is black, and the pixels that are closest to 255 are the brightest, where 255 is white.

The data obtained by the Open IA AI tool was then subjected to an analysis using the one-way analysis of variance (ANOVA) statistical test. This was performed on each of the histograms in order to assess whether there were any significant differences between each of the samples. In addition, the mean, light and dark values of the selected images will be calculated for both discourses (Koeing et al., 2012). This process will be performed systematically on all selected frames (Atkinson, 2014; Fell et al., 2021).

Despite the fact that a number of recent studies (Abrar et al., 2021; Grover et al., 2021; Walter and Hellström, 2021) have analysed luminance curves for various purposes (Chen et al., 2021; Karmakar et al., 2021; Lu et al., 2021), there is currently a paucity of research that has examined the differences and similarities of political messages, particularly in the context of the attack on the Capitol Hill by Donald Trump and Joe Biden.

A qualitative methodology is also employed, the basis of which is the content of the speeches. The initial phase of the research will entail the transcription of the texts of each politician, followed by analysis with the AI tool ONEAI. The application under scrutiny here analyses the potential for hate messages to be conveyed by politicians, highlighting the most frequently used words and their order. In this section, the transcript of one additional speech, that of Donald Trump, delivered prior to the assault on the Capitol, will be included. This speech will also be analysed with the assistance of artificial intelligence. In this discourse, we will refrain from drawing parallels between this speech and those delivered by Biden, given that the president-elect did not hold a rally, in contrast to Trump's rally held in the period preceding the assault.

Figure 1. Part of the sample chosen for this quantitative analysis of Donald Trump's and Joe Biden's speeches on the assault on Capitol Hill.

Source(s): Own elaboration, 2024.

6. Analysis and Results

The results of the histogram analysis of the selected sample in the Trump speech are as follows: the ANOVA analysis performed on the luminance histogram data of each frame has resulted in a very low F-statistic (0.007513) and a P-value of 1.000000. This finding suggests that there are no substantial disparities between the luminance distributions of the various frames (Figure 2). In other words, the luminance histograms of the frames are very similar to each other, suggesting that the luminance is distributed fairly consistently across the frames.

Figure 2. Sample of one of the images from the analysis of Trump's speech (left). Frequency (X-axis) of each pixel value (0-255) (Y-axis) in the mean of the Trump speech images (right).

Source(s): Own elaboration, 2024.

Conversely, the distribution of highlights, mid-tones and shadows was as follows: shadows (0-50) at 25.38%; mid-tones (51-199) at 43.38%; and highlights (200-255) at 31.24%. Mid-tones (51-199) account for 43.38% of the pixels, indicating that a considerable portion of the images contain details with moderate brightness levels. This range of tones typically encompasses skin colours, background tones, and other areas that are neither excessively bright nor excessively dark. It is noteworthy that the highlights (200-255) constitute 31.24% of the pixels, a proportion that is of considerable significance. This finding indicates the presence of numerous bright areas within the images, including well-lit surfaces, reflections, and white elements. In comparison to shadows, the presence of a high proportion of highlights has the potential to imbue images with a heightened sense of brightness or lustre. As can be deduced from the data, shadows (0-50) represent 25.38% of the pixels. While not constituting the majority proportion, this finding remains salient, signifying that the images encompass areas of darkness or low-light intensity, albeit not to a significant extent.

It is evident that the images have been meticulously balanced in terms of brightness, thereby ensuring optimal representation of both light and dark areas. This phenomenon could be indicative of either more even lighting or image processing techniques that are designed to preserve a broader dynamic range.

The results of the histogram analysis of Biden's speech are as follows: the analysis of variance (ANOVA) performed on the luminance histogram data of the new frames has resulted in a very low F-statistic (0.00015) and a P-value of 1.00000. This finding suggests that there are no substantial disparities between the luminance distributions of the various frames within this novel dataset. As was the case in the preceding instance, the luminance histograms of the frames are found to be highly analogous, thus indicating a uniformity in the luminance distribution across the frames.

In contrast, the distribution of highlights, mid-tones and shadows is as follows: shadows (0-50): 81.62%; mid-tones (51-199): 17.37%; and highlights (200-255): 1.01% (Figure 3).

Figure 3. Sample of one of the images from the analysis of Biden's speech (left). Frequency (X-axis) of each pixel value (0-255) (Y-axis) in the mean of the Biden speech images (right).

Source(s): Own elaboration, 2024.

This results in images characterised by a prevalence of dark tones, with minimal presence of bright or white elements. The potential causes of this phenomenon include the lighting conditions present in the scene, the content of the images (for example, the presence of dark backgrounds or individuals attired in dark clothing), or the way the video was captured or processed. Furthermore, the absence of a broad spectrum of brightness may signify that the images exhibit constrained contrast, characterised by a muted distinction between darker and lighter regions. The employment of a dark tone may be attributed to the intention of creating an atmosphere or conveying a particular message, thereby evoking a sense of seriousness, solemnity, or focus on the subject matter rather than the environment.

Conversely, an analysis of the content of the speeches using the IA ONEAI application yielded the following results. The following words were most frequently used by Trump in his post-assault on the Capitol speech: The following terms were used: “America” (3), “law” (3), “citizens” (2), “family” (2), “violence” (2), “economy” (2), “lives” (2) and “country” (2). With regard to the emotions identified by AI ONEAI, it is notable that only a single negative emotion is detected. Regarding allusions to particular concepts, the following were identified: dates (2), numbers (2), specific locations (2) and organisations (1).

In Biden's speech following the Capitol assault, a reduced number of words were observed, with the most prevalent being “today” (7), “democracy” (7), “America” (6), “Capitol” (5), “people” (5), “president” (5), “assault” (5), “good” (4), “chaos” (4), “work” (5), “nation” (3), “God” (4), “way” (4) and “words” (3). This is a more extensive range of words, resulting in a single phrase that is characterised by negativity, but not by toxicity or vindictiveness. Direct allusions to concepts are concentrated in locations (8), dates (9), people (3) and political groups (4).

Finally, and additionally, Trump's speech prior to the assault on the Capitol yields the following results. The most frequently recurring lexical items are: “people” (31 instances), “election” (19 instances), “country” (20 instances), “years” (15 instances) and “president” (11 instances). Furthermore, the presence of toxic content was identified in 11 sentences, while 10 sentences exhibited characteristics of vindictive content. With regard to direct allusions, 49 individuals, 18 political groups and 16 specific locations were identified, including cities and notable buildings such as the White House and the Capitol. In this speech, in contrast to the other two, the AI application has been configured to identify content that is toxic and/or hateful. It is important to note that this was Donald Trump's rally prior to the storming of the US Capitol by a crowd of his supporters.

7. Discussions

Following an independent analysis of the two speeches on the Capitol assault by Donald Trump and Joe Biden, it was concluded that there is a correlation between the images in each of the videos. In both cases, the audiovisual production focused on depicting each politician with minimal or no framing or camera movement. Furthermore, the politicians' physical movement was minimal during the speeches, contributing to a consistent and unvarying visual impression. These issues are reflected through the results of the statistical regression analysis. The F-statistic and P-value of 1.000000 in both videos indicate that there were hardly any differences in luminance between the analysed frames.

Despite the divergent ideological orientations of the two politicians in question, the analytical findings reveal a striking similarity in the aesthetic treatment employed in their respective messages. The correlation of the images analysed in both speeches reveals a similarity in the way political content is narrated. This finding aligns with the conclusions of earlier studies (Hallin and Mancini, 2004; Plasser and Plasser, 2002), which highlighted the uniformity in the processing of information exhibited by politicians from disparate ideological backgrounds. As posited by other authors (Cerdán Martínez and Padilla Castillo, 2019; Villa-Gracia and Cerdán, 2020), the models employed for the narration of political issues differ from those utilised in other audiovisual media, including films, documentaries, advertisements and video clips. In the former, the emphasis is on the visual representation of the politician, with a pervasive presence. In the latter, a diverse array of elements contributes to a more dynamic depiction of the character.

Conversely, a comparison of the results of the luminance averages of both videos revealed some discrepancies. A comparison of the lighting in the videos of Donald Trump and Joe Biden reveals a notable distinction. In Trump's video, the lighting is characterised by a prevalence of high-intensity lighting, while in Biden's video, the lighting is of a lower intensity and is focused on low-intensity lighting. As asserted by Place and Peterson (1974), this phenomenon can result in disparities in the transmission of emotions to the audience. High levels of luminance would be classified as high key. In the domain of photography, the term is employed to elicit sensations of serenity and tranquillity. In the event of the luminance values being low, the result is referred to as low key. The term "low key" is associated with tension, emotional intensity and majesty (see Hemphill, 1996; Meier et al., 2017). Conversely, Donald Trump presented a more distinct image than his opponent, a strategy that, according to several authors (see Hemphill, 1996; Meier et al., 2017), was intended to generate an appeasing discourse, particularly in light of the gravity of the Democratic accusations following the assault on the US Capitol.

Furthermore, both appearances exhibited a congruent trajectory regarding audiovisual editing. In both Biden's and Trump's appearances, most of the video was transmitted through a medium shot, without cuts to a second camera. It was only at a few specific points that a wide-angle view and a medium-angle view were shown from different angles. This finding aligns with the observations of other researchers (Barrientos et al., 2019; Morris, 2017) who have asserted that, despite the utilisation of multiple cameras, the image processing remained as straightforward and uncomplicated as possible.

A plethora of studies have investigated the content of televised debates in different electoral campaigns (Barrientos et al., 2019; Benoit et al., 2003; Morris, 2017; Padilla Castillo, 2014; Téllez et al., 2010; Valdez-Zepeda and Huerta-Franco, 2009). It has become increasingly prevalent for political candidates to reach a consensus with the media regarding the management of their image. The methodology employed in this study, predicated on the analysis of luminance curves, would furnish us with a mathematical result on the degree of similarity of the images of each politician, thereby confirming this fact.

It is evident that a discernible divergence in content is present, which is indicative of a parallel aesthetic approach. While Biden's appearance suggests a moderate tendency, Trump's two appearances exhibit a clear vindictive component and a toxic tendency, particularly the one prior to the assault on the Capitol. This phenomenon is also evident in the spectrum of words used by each of the candidates. It is evident that Trump's vocabulary is limited, which consequently manifests in a direct, redundant and unelaborated discourse. Biden's approach is more expansive in both conceptual and thematic terms, seeking to encompass a range of perspectives on the issue. Conversely, Trump persistently employs populist rhetoric, employing terms such as "people," "country," and "election" to foster social mobilisation. In contrast, Biden employs concepts such as "democracy" and "America" in his discourse, thereby fostering a more moderate and nuanced dialogue that is significantly more distant from positions of toxicity.

In conclusion, it can be posited that, despite the minimal aesthetic variation exhibited by both speeches, Biden's speech evinces a propensity towards understatedness. This approach conveys a sense of drama that is not reflected in the content, which is much more subdued than that of Trump's speech prior to the assault. With regard to Trump's post-assault speech, it is notable that the key remains high, in contrast to the trend detected by the IA ONEAI application in his pre-assault speech. Consequently, both candidates employed an aesthetic that diverged from their previously adopted position, suggesting a propensity for dramatic compensation through the medium of image. Trump evokes an aesthetic characterised by concepts such as joy and optimism. Conversely, Biden adopts a more subdued approach, which serves to highlight the dramatic elements of the content. Both positions are characterised by an attempt to establish equilibrium, seeking to embrace a broader spectrum of emotions.

It is imperative to emphasise several limitations of the present study. Initially, the analysis performed focuses on a chronological sample that attempts to represent the aesthetics of each video in a generic way. Secondly, the resolution of the samples of luminance curves collected for each frame could be extended in future studies in order to achieve greater precision in the analysis. Although luminance is a determining factor in the videos, the importance of colours has yet to be studied through quantifiable data, which are not specified in this study.

In conclusion, it is asserted that, notwithstanding its limitations, this research provides a novel methodology for the analysis of political speeches and/or audiovisual works. Furthermore, it paves the way for the development of future software capable of analysing videos in real time, thereby facilitating the estimation of similarities and differences with previously studied material.

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