


# Attitudes Towards Global Warming on Twitter: A Hedonometer-Appraisal Analysis

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## ABSTRACT

Public opinion surveys over the past 30 years show that public opinion is split on the issue of global warming. One of the problems with “solicited” opinion polls is that the findings may be selectively interpreted in favour of the political goals of a particular interest group. To gain a better understanding of the general public’s unsolicited responses to climate change news, the current study examined Twitter messages containing the words “global warming” spanning 16 months. Using a framework combining a sentiment analysis technique, Hedonometer from the perspective of natural language processing and appraisal theory from a discourse analysis perspective, the study shows that the demonstrated happiness level in tweets containing the words “global warming” is consistently lower than the general level on Twitter due to increased use of negative words and decreased use of positive words. The appraisal analysis shows that “Appreciation” is used most frequently and “Affect” least.

## KEYWORDS

Appraisal Theory, Attitude, Global Warming, Hedonometer, Sentiment Analysis, Twitter

## INTRODUCTION

As one of the major concerns worldwide, global warming and its consequences have prompted exhaustive discussion in academic literature and the media, from traditional media such as newspapers to new media such as Twitter and Facebook. As the media plays a critical role in shaping the public’s views by driving and perpetuating concepts and opinions, many studies focus on global warming reports in newspapers from the perspective of topical prevalence over time (Bohr, 2020), linguistic patterns in global warming reports (Dayrell, 2019), or influence of news reports on public understanding (Jang, 2013). However, the arrival of the digital age and the rise of social media have attracted academic attentions from traditional forms of unidirectional communication such as the print press or television to new ways of bidirectional interaction such as Facebook, YouTube and Twitter. Besides, the previous age of mass communication disseminating information to the public has evolved into self-communication which communicates with oneself. This results in media discourse transforming from merely “a unified, generic ‘hypertext’” to a “diversified, individualised ‘mytext’” (Castells, 2013, p. xx). Social media allows users to share their opinions and attitudes alongside various

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sources that contribute to the public's response to current issues. Increasing acknowledgement of the significance of the public's perception of global warming, which is essential for the formation of public attitudes to this issue and changes of social practices as well as policymaking, has led to more scholarship on social media discourse. Use of sentiment analysis on global warming is now one of the leading ways to ascertain the general polarity of a given text. However, mere awareness of this polarity is not enough for discourse analysis, which requires a greater level of specificity, such as the linguistic representation of global warming in social media. Besides, subjective involvement and use of relatively small data sets, and the "cherry-picking" phenomenon (only choosing supporting content as evidence to support a point), are often criticised in the literature of linguistics (Baker et al., 2008). Thus far, insufficient scholarly attention has been paid to the linguistic representation of global warming in terms of attitudinal statements while considering the general polarity of a large amount of data.

In order to fill this gap in the literature, the present study explores messages concerning global warming on Twitter, one of the most popular social networking platforms, by applying big data analytics for discourse analytic purposes and proposing a new framework: the combination of Hedonometer and Appraisal Theory. The sentiment analysis technique Hedonometer is responsible for the general tendency toward global warming on Twitter and Appraisal Theory for scrutiny of linguistic realisation. By applying a text-mining technique and traditional discourse analysis method, it is possible to meet both demands of grasping details of linguistic representation and general polarity of considerable data avoiding manually laborious work as well as "cherry-picking" phenomenon.

The paper makes the following main contributions. First, the research shows the possibility of combining sentiment analysis technique and linguistic theory. Specifically, the newly proposed framework constructs a complementary role for each other by combining Hedonometer and Appraisal Theory. As mentioned earlier, the framework maximizes benefits and minimizes disadvantages of both. Second, the research demonstrates the general attitudes towards global warming on social media and how the attitudes are conveyed in language, which is, heretofore, the first attempt in the literature of attitude analysis. Third, the research contributes to the sociological and psychological studies by confirming the negative bias phenomenon and analysing different perspectives taken in the use of person, respectively. The present paper is structured into two procedures. The first procedure provides an overview of public opinions toward global warming on Twitter between January 2020 and April 2021. It employs Hedonometer to indicate attitudinal polarity, and word shift graphs to analyse specific words contributing to the polarities and how they do so. The second procedure scrutinises how public attitudes are presented on Twitter using Appraisal Theory, examining linguistic features in detail.

## **LITERATURE REVIEW**

Anthropogenic global warming is a global concern with global consequences. Knowledge of global warming is principally circulated through public communication, such as news media. Media coverage is the primary way to strengthen the awareness of global warming and disseminate information for the public. An array of literature explored the relations between media and global warming, mainly concentrating on newspaper coverage before the flourishing of social media.

Public debate indicates the significance of the theme, the opinions and preferences of the society, which is very important for policymaking and changes in social practices. Research shows that public opinion is influenced dramatically by newspapers which is the "elite discourse" (Bohr, 2020). In other words, the information disseminated to the public relies heavily on elite cues disseminated through frame building. Apparently, the voices of the masses were neglected when there was no platform for individual voices.

With the arrival of the digital age, social media have mushroomed, especially Twitter, allowing the voicing of individual preferences, opinions, and concerns and providing valuable information sources. Social media embody the feature of self-communication that is "self-generated in content,

self-directed in emission, and self-selected in reception” (Castells, 2007, p. 248). The very individual text on Twitter has attracted the attention of researchers interested in the personal expression of ordinary people. Academic attention to public perception of global warming has now shifted from traditional media to social media, Twitter in particular.

The literature on global warming and Twitter data has the following main focuses. One of the most prominent aspects of global warming is the politicisation of the issue of global warming. With the decline of traditional media and the boom of social media, social media, particularly Twitter, have become vital spaces for political communication (Vakeel & Panigrahi, 2018). Recently, Buccoliero et al. (2020) observed that Twitter strongly influenced the 2016 US presidential election. Not surprisingly, increasing academic attention has been paid to tweets in an attempt to find connections between political views and global warming. For example, Hajibagheri and Sukthankar (2014) examined political polarisation over global warming by assessing tweets and confirmed the conclusions of McCright and Dunlap (2011) that self-identified liberals and Democrats tended to convey personal concern about global warming.

In the discussion of global warming and politics, one inevitable topic is the differences and connections between “global warming” and “climate change”. They are two terms referring to the same phenomenon, interchangeably used by media, which are however slightly different in meaning. Semantically, “global warming” indicates the Earth’s rising surface temperature, while “climate change” has a broader meaning, a range of climate changes caused by overall rising temperature. The former evokes strong associations of human causation, while the latter evokes strong associations of natural causation (Whitmarsh, 2009). Previous studies showed that the two terms had different political connotations. For instance, Schuldt et al. (2011) conducted an analysis of partisan websites and found that conservatives favoured the term “global warming” and liberals favoured “climate change”. However, “global warming” is selected in the study purely for the sake of research of environmental concerns of the public on this respect without reference to its comparison with “climate change”.

As many researchers have noted, abnormal weather events and natural or human-caused disasters can influence society’s attitudes to global warming (Cody et al., 2015). Much literature concerns the relations between specific disasters and global warming. Generally speaking, abnormal weather and disasters have a significant effect on the number and intensity of tweets. Put another way, abnormality in nature usually ignites the discussion over global warming on Twitter. A series of researchers have confirmed this point. For example, considering Twitter users as “distributed sensors” that can offer real-time information about current events, Kirilenko and Stepchenkova (2014) discovered that the major events, whether global or local, affected the intensity of discussion about global warming.

Closer to the topic of the current paper, the exploration of general beliefs, attitudes and emotions about global warming, known as sentiment analysis or opinion mining, has become one of the leading research branches benefiting from the development of big data analytics tools (Iftikhar & Khan, 2020; Kirelli & Arslankaya, 2020; Qiao & Williams, 2022). Since the detection of polarity is the primary aim of sentiment analysis, part of the literature focuses on the polarity of Twitter data pertaining to global warming, including Dahal et al. (2019) who investigated 390,016 tweets about global warming using sentiment analysis and found that the overall discussion of global warming had negative polarity.

Though plentiful studies have inspected prevailing beliefs of global warming in terms of Twitter data, a gap still exists in the literature: the existing literature provides only a general conclusion of prevailing sentiment without specifically linguistic details. In other words, how social media users express their positive or negative attitudes is still unknown. Consequently, different from the previous studies on attitude, the present study aims to explore how the masses express their attitudes in language through Appraisal Theory apart from the analysis of public attitudes through sentiment analysis. The research considers both general polarities based on substantial data and circumstantial linguistic realisation.

## Theoretical Framework: Hedonometer Analysis and Appraisal Theory

The present study proposes a new framework combining Hedonometer and Appraisal Theory. Basic descriptions of these are provided below.

### • Hedonometer

As one of the text-mining techniques in natural language processing (NLP), text analysis, and computational linguistics, sentiment analysis (also known as opinion mining), can extract opinions and emotions from the text under analysis, identifying the polarity of the text as positive or negative (Stine, 2019). Studies based on sentiment analytic techniques have become increasingly popular in recent years in a vast array of topics. Hedonometer is a sentiment analysis technique that measures the happiness demonstrated in an extensive collection of texts. It assigns sentiment scores to individual words based on a wordlist of 10,222 unique words by merging the most frequent 50,000 words rated by using Amazon's Mechanical Turk online marketplace from four disparate corpora, viz. Twitter, Google Books, the New York Times and music lyrics (Dodds et al., 2011). The happiness score ranges from 1 (*least happy*) to 9 (*most happy*). By extracting word frequency in a given text  $T$  and assigning scores to words, Hedonometer can compute the weighted average happiness of a given text through Equation (1) (Dodds et al., 2011).

$$h_{avg}(T) = \frac{\sum_{i=1}^N h_{avg}(w_i) f_i}{\sum_{i=1}^N f_i} = \sum_{i=1}^N h_{avg}(w_i) p_i \quad (1)$$

where  $w_i$  is a given word in the text,  $f_i$  is the frequency of the  $i$ th word  $w_i$ ,  $N$  is the number of unique words,  $h_{avg}$  is the average happiness,  $h_{avg}(T)$  is the average happiness of the whole text,  $h_{avg}(w_i)$  means the average happiness of the word  $w_i$ , and  $p_i = \frac{f_i}{\sum_{i=1}^N f_i}$  is the normalised frequency.

The ability to assess whether a text is positive or negative is one of the most notable contributions of sentiment analysis. However, mere knowledge of polarity is not the final stop for text mining. The exploration of specific words which contribute the most to the overall emotions of text is also one of the goals. Hedonometer allows us to discover those specific and essential words and examine how they shape the general content using sentiment analysis as a lens (Reagan et al., 2017).

Hedonometer analysis often involves two texts. One is a reference text, one a comparison text. The texts are compared in terms of happiness score due to changes of word frequency. A word shift graph is a visualisation method that shows changes of word frequency and difference in happiness level between two texts by ranking words according to their contribution to the change of average happiness in absolute decreasing order, from largest to smallest. Equation (2) explains how the word shift graph is computed:

$$\delta h_{avg,i} = \frac{100}{|h_{avg}^{(comp)} - h_{avg}^{(ref)}|} \left[ \underbrace{h_{avg}(w_i) - h_{avg}^{(ref)}}_{+/-} \right] \left[ \underbrace{p_i^{(comp)} - p_i^{(ref)}}_{\uparrow/\downarrow} \right] \quad (2)$$

where  $T_{ref}$  is the reference text,  $T_{com}$  is the comparison text, with corresponding average happiness scores  $h_{avg}^{(ref)}$  and  $h_{avg}^{(comp)}$ ,  $\delta h_{avg,i}$  means the happiness shift of the  $i$ th word,  $h_{avg}^{(comp)} - h_{avg}^{(ref)}$  indicates the relative increase or decrease in the use of a positive or negative word.

Hedonometer has been shown to be robust in text-mining since its first trial of analysing happiness trends in songs, blogs and presidential addresses (Dodds & Danforth, 2010) and further explained by studying happiness trends on Twitter (Dodds et al., 2011).

- **Appraisal Theory**

As an extension of the interpersonal dimension of Systemic Functional Linguistics, the Appraisal framework evaluates language by developing three systems with consideration of the intersubjective stance of writers or speakers, i.e., Attitude, Engagement and Graduation (Martin & White, 2005).

Attitude is related to individual's feelings, including emotional reactions, judgements of behaviour and evaluation of things, covering three areas, viz. emotion, ethics and aesthetics. Correspondingly, it consists of three sub-types, i.e., Affect (emotion), Judgement (ethics), and Appreciation (aesthetics). The Affect examines positive and negative emotions, containing three major subset emotion groups: un/happiness, in/security, and dis/satisfaction. Un/happiness is concerned with moods of feelings -- happiness, sadness, hate, and love. In/security involves peace and anxiety feelings connected to surroundings, such as anxiety and confidence. Dis/satisfaction covers feelings concerned with achievement and frustration, for example, caution or compliments. Judgement deals with positive or negative assessment of people's behaviours according to different social norms, values or laws. It can be subdivided into social esteem and social sanction. The former is related to normality (e.g., normal, eccentric), capacity (e.g., robust, weak) and tenacity (e.g., careful, hasty), and the latter involves veracity (e.g., honest, lie) and propriety (e.g., good, bad). Finally, appreciation has to do with the evaluation of things, and contains three classifications: human' reactions to things (e.g., exciting, flat), composition (e.g., balanced, simple), and value (e.g., deep, shallow). Engagement is related to the dialogic stance of the writer or speaker. Graduation deals with the scalability (upscaling and downscaling) of attitudinal meaning.

As the present study aims to discover how language users convey their views and emotions rather than the dialogic stance which can be analysed by Engagement or intensity of language by Graduation, only the Attitude system is applied here to analyse public attitudes to global warming. What's more, Attitude is believed as the most direct and fundamental way to express opinions and evaluation (Aloy Mayo & Taboada, 2017).

As an essential theory in linguistics, Appraisal Theory has been employed in a wide spectrum of studies on opinion detection, such as wine review (Hommerberg & Don, 2015), news review (Cavasso & Taboada, 2021), consumption review (Hommerberg, 2015), to name but a few.

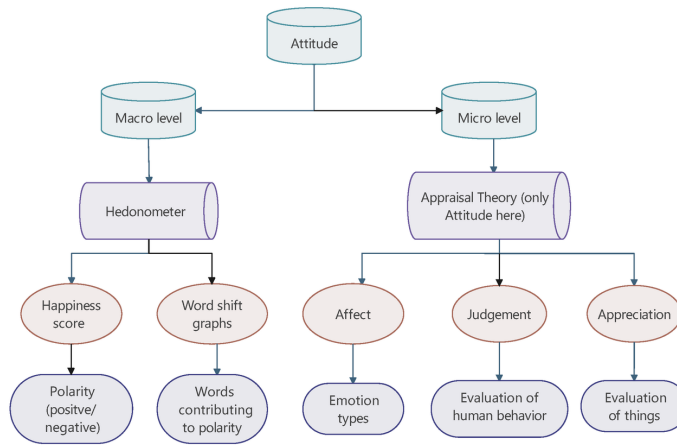
- **Combination of Hedonometer and Appraisal Theory**

The basic ideas behind this combination are as follows. First, the application of Hedonometer as a lens offers a panorama of attitudes; Second, based on the general attitudes provided by Hedonometer, Appraisal Theory provides detailed linguistic patterns. As Figure 1 shows, the proposed framework of analysing attitude works on two levels. Hedonometer is responsible for the macro level to gain a general tendency through happiness score and word shift graphs. The polarity is obtained by comparing happiness scores. Lower score indicates more negative in valence, and vice versa. The word shift graphs further explain how the polarity is made in terms of words. On the micro level, the use of Appraisal theory (only Attitude here) can provide more linguistic details through Affect, Judgement and Appreciation.

The advantages of this framework are as follows: firstly, use of the data-mining technique Hedonometer can avoid one of the shortcomings of relatively small data in traditional discourse analysis, which may result in the incompleteness of results. By processing a large number of data, it is easy to ascertain a general tendency of attitudes. Moreover, Hedonometer provides specific

words contributing most to the change of happiness level based on word frequency and individual happiness score, similar to the “keywords” analysis in discourse analysis but adding another layer of happiness score to attitudinal meaning analysis. The first step of big data processing is expected to reduce subjectivity in discourse analysis, which is often criticised for “cherry-picking”.

Figure 1. Proposed framework



However, the disadvantage of Hedonometer analysis cannot be ignored if applied in discourse analysis. Hedonometer, in essence, is an algorithm based on specific sets of words, which means the neglect of context, though it will not influence its robustness in dealing with a large amount of data. The context-based analysis of Appraisal Theory supplies this gap. Appraisal analysis (of which only the Attitude system is used here) helps create a further and more elaborate explanation and confirmation for the first step with consideration of general tendency. By virtue of the second step, it is possible to categorise emotion types (by Affect) and find assessment standards for people’s behaviours (by Judgement) and things (by Appreciation). This is the second advantage of this framework.

In conclusion, the first step sets general parameters for the second step and compensates the deficiency (laborious manual work) of the second, while the second step offers a detailed explanation for the first and compensate the deficiency (lack of linguistic details) of the first. Thus, they are complementary.

## METHODOLOGY

The data were crawled by Python from Twitter’s gardenhose Application Program Interface (API). All tweets containing the keyword “global warming” were collected. The extracted dataset comprises 495,231 tweets with over 20 million words spanning 16 months (January 1, 2020, to April 30, 2021).

In order to improve data quality, data cleaning is necessary through deleting errors (e.g., wrong spellings) and inconsistencies. These tweets must be related to the original meaning of global warming—the warming of the Earth system, rather than metaphorical meaning of the term. Such tweets as “Girls are hot. Boys are hot. Why is everyone so hot? Global warming” were deleted from the dataset. It is also necessary to remove emojis as they are not part of this study and punctuation marks including the colon (:), slash (/), question mark (?), and full stop (.), since they do not contribute meaning

to wordlist-based sentiment analysis. Unlike other sentiment analysis techniques, Hedonometer avoids stemming or lemmatisation due to its algorithm. Verbs, in particular, have different scores for different inflected forms, for example,  $h_{avg}(\text{help}) = 6.08$ ,  $h_{avg}(\text{helps}) = 6.6$ ,  $h_{avg}(\text{helped}) = 7.28$ ,  $h_{avg}(\text{helping}) = 7.18$ . This is one of the reasons that Hedonometer is the most desirable technique for measuring sentiment in discourse analysis. The change of tense is not just about the difference in temporal information. Often, it denotes semantic relations and attitudes (Declerck, 2015). The state of action influences the happiness score. For instance, “help” is a positive word, “helping” suggests assistance ongoing, and “helped” indicates the end of assistance action, probably with a better result. Consequently, it is not difficult to understand why “helped” has the highest score.

Two different analytic methods are involved which corresponds with the above-mentioned processes. The Hedonometer part followed the research pattern by Cody et al. (2015). Clearly neutral words (with happiness score ranging from 4 to 6) were omitted in the calculation of happiness for a better view of polarity. The words “global” and “warming” have score of 6 and 5.58, respectively. For the purpose of comparison, a random 10,000 or so tweets from each month were collected for use as the reference text from all tweets (unfiltered data) from January 2020 to April 2021. The comparison text is the tweets containing the keyword “global warming”. Word shift graphs are applied to compare the average scores of happiness of the two texts and show specific words contributing most to the change of happiness level. Lastly, the study focuses on two events: the hottest recorded temperature in Antarctica (February 2020) and Hurricane Laura (August 2020), as examples of the connection between happiness level and specific topics.

It is not practical to analyse all 20 million words from the collected data for the second part, as applying the Attitude system in Appraisal Theory based on context requires manual annotation with complicated details. For practicality’s sake, sampling was employed here through a random collection of 500 tweets. The data was annotated and organised in the UAM CorpusTool. The annotation followed two principles proposed by Cavasso and Taboada (2021): minimality and contextuality. Minimality means the shortest unit, or *span* as Cavasso and Taboada refer to it, annotated to show attitudinal information. The length of the unit can vary from a single word to a whole sentence. Contextuality means the consideration of context when identifying the categories that attitudes and polarities belong to.

The study involves three categories of Attitude, i.e., Affect, Judgement, and Appreciation and two polarities—positive and negative. This Attitude analysis focuses on the frequency and distribution of Attitude, as well as detailed linguistic features.

## RESULTS AND ANALYSIS

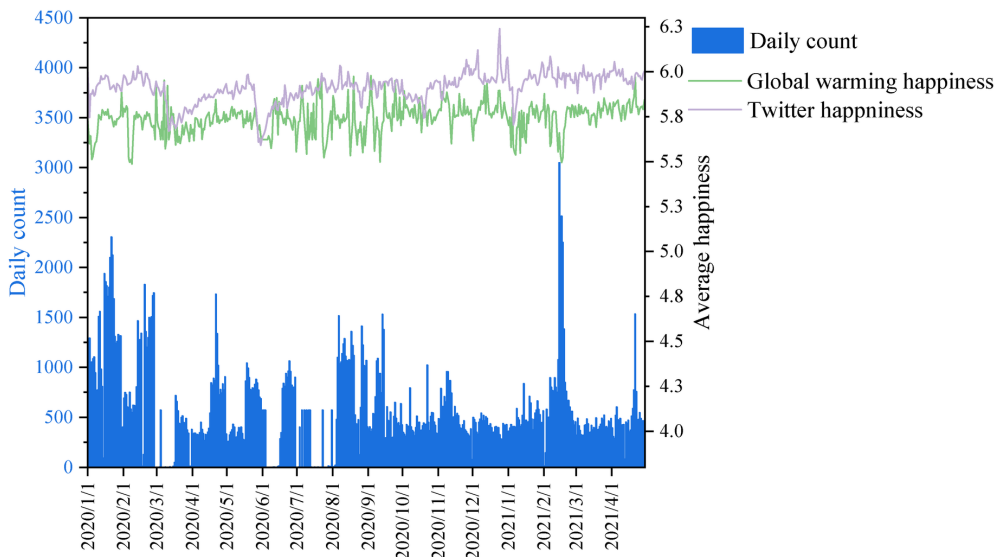
Accordingly, this part is divided in two, i.e., Hedonometer analysis and Appraisal analysis. The general procedure is from the macro-level to micro-level, from wholeness to facts. Hedonometer analysis was conducted first to grasp a general happiness tendency toward global warming and attitudes to the issue. Having obtained the general polarity at a macro level, the micro-level of Appraisal analysis proceeded to gain a linguistically specific presentation of the public’s opinions.

### • Hedonometer analysis

The data ranging from January 1, 2020, to April 30, 2021, were processed by the Hedonometer algorithm in Python. The daily raw frequency of tweets containing the keyword “global warming” over the period (Figure 2) shows several peaks, including January, February, and August 2020, and February 2021. A close examination of the peak time reveals that the tweets focus on four environment-related issues respectively, viz. Australian wildfire, the hottest recorded temperature in Antarctica, hurricane Laura and winter storm in Texas.

Figure 2 shows the average daily happiness of tweets containing “global warming” and general tweets (random 10,000 tweets each month from all tweets). As Figure 2 indicates, the average happiness level of tweets containing “global warming” is, in general, consistently lower than that found in the whole Twitter data. However, some outlier days occur when the average happiness level of “global warming” tweets is higher than general Twitter. Two circumstances explain this: the first is that some words with relatively high happiness scores appear more frequently in global warming tweets, for example, on September 6, 2020, words like “significant” ( $h_{avg} = 6.82$ ), “improvement” ( $h_{avg} = 7.08$ ), and “process” ( $h_{avg} = 7.26$ ) in tweets talking about Joe Biden’s climate plan have more occurrences than usual; the second is the relatively low average happiness level of all Twitter data, for example, May 30, 2020 is the saddest day during the research period with happiness score 5.63 due to the protests against police brutality in response to the death of George Floyd. However, the outliers are not important for the whole trend of global warming (Cody et al., 2015).

**Figure 2. Daily raw frequency of tweets containing “global warming” and daily average happiness of global warming and whole Twitter**

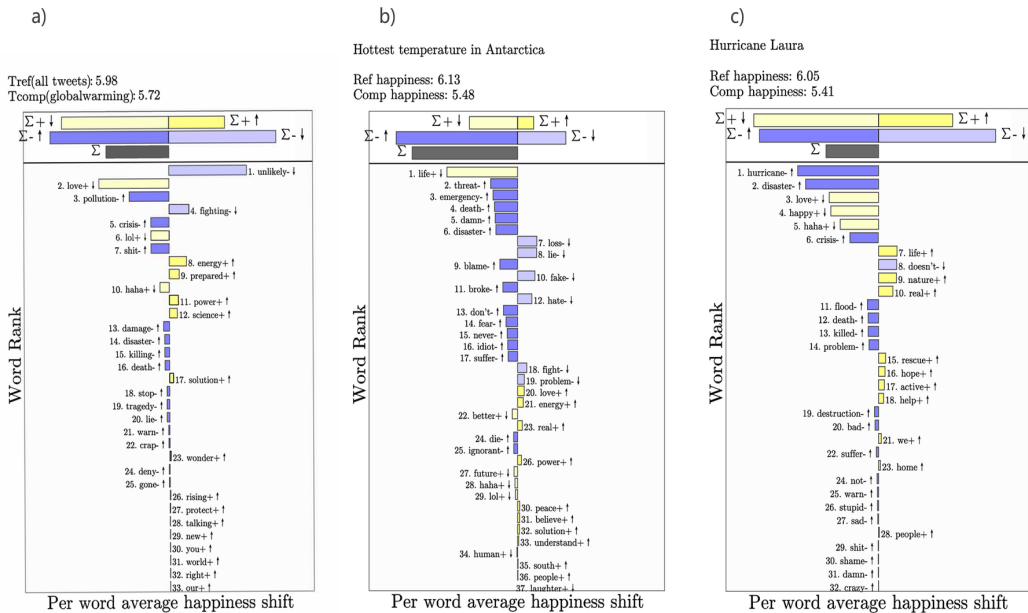


With the tweets containing “global warming” from January 2020 to April 2021 as the comparison text, and a collection of a random 10,000 tweets each month over the research period as the reference text (referred as all tweets here), the Hedonometer results in Figure 3 (a) show the specific words contributing most to the change in the happiness levels of the global warming tweets and the reference tweets. In line with Figure 2, Figure 3 (a) shows that the total happiness score of the reference text (all tweets) is 5.98 when the comparison text (global warming tweets) is 5.72. The relatively low score of the comparison text is attributable to an increase of negative words and a decrease of positive words.

On the left, the decrease in the word “love”, which has a high happiness score of 8.42, and the increase of “pollution” with a low happiness score of 2.16, contribute most to the negativity of tweets containing the words “global warming”. Global warming, per se, is not necessarily connected with “love” or any other pleasant words like “lol” ( $h_{avg} = 8.42$ ) or “haha” ( $h_{avg} = 7.64$ ), which are on the left side, also showing a decrease in the happiness score in the global warming discussion. The word



Figure 3. Word shift graphs for global warming tweets<sup>1</sup> (a) Word shift graph comparing global warming tweets to all tweets, (b) Word shift graph for hottest temperature in Antarctica, (c) Word shift graph for hurricane Laura



“pollution” is closely related to global warming; these are the two main environmental issues for most net citizens. This is demonstrated in the tweet “Global warming getting intense, pollution getting worse, polarisation among people is rising, so what makes you think that 2021 gonna be better than 2020?”. Profanity like “shit” ( $h_{avg} = 2.5$ ) and “crap” ( $h_{avg} = 3.34$ ) shows an increase in the discussion of global warming, such as the tweets “Fuck your global warming is fake shit. Oh, Australia has been on fire since Sep. 2019?”, “2020: what? Did you forget about global warming amidst all the other crap I’ve been throwing at you people? Ha!”. The use of negative words like “crisis” ( $h_{avg} = 2.48$ ), “damage” ( $h_{avg} = 2.58$ ), “disaster” ( $h_{avg} = 1.96$ ), “tragedy” ( $h_{avg} = 2.06$ ) also contributes to the low happiness level. These words are partly used in a metaphorical way, as in the tweets “it’s a real tragedy and no one is doing nothing! Global warming.”, and partly used in causal relationships, like “2020, there are countless disaster occurred though, fundamentally the global warming caused these. We have to take this fact seriously.” On the one hand, twitters think global warming is an emergency humans need to face; on the other, global warming can cause further severe issues. Words like “lie” ( $h_{avg} = 2.6$ ) and “deny” ( $h_{avg} = 3.44$ ) appeared more often in discussing global warming issues, which primarily attributes to the “Hoax frame” (certain community believe global warming is just a lie) (Heerschop et al., 2011). Words like “killing” ( $h_{avg} = 1.7$ ) and “death” ( $h_{avg} = 1.54$ ) indicating adverse results from global warming also occurred more frequently, as in the tweet, “Today telling people how this fossil bank INCREASED investment in fossil fuels in 2020 = more Co2 = more global warming = more destruction and death.”

On the right half of Figure 3 (a), the decreased use of the negative words “unlikely” ( $h_{avg} = 3.48$ ) and “fighting” ( $h_{avg} = 2.76$ ) are shown in the first two rows in the increase in happiness section. At the same time, some more positive words like “energy” ( $h_{avg} = 7.22$ ), “prepared” ( $h_{avg} = 6.74$ ), “power”

( $h_{avg} = 6.68$ ), “science” ( $h_{avg} = 6.86$ ), “solution” ( $h_{avg} = 6.84$ )” are used in global warming tweets. These words are mostly affiliated with methods of solving the global warming problem. The word “energy” in relation to topics such as energy consumption and forms of energy sources is often connected with global warming when talking about causes of global warming and solutions to it, for instance, “In 2020, an amazing 80% of new energy capacity came from renewable sources...What we do in this decade will be critical to limiting global warming.” The word “power” is often connected with electricity generation such as wind power and solar power, as in the tweet, “Green power up. Global share of wind and solar energy has doubled since 2015 and made up 10% of electricity so far in 2020. While the world driving closer to climate goal to limit the worst effects of global warming, Nigeria moving towards fossil fuels.” The same is true of political power, as many believe global warming is a politician-driven issue, as in “Not only loopholes, but political operatives, used real and perceived threats to seize power. Today the pandemic and global warming are all about seeking political power.” Science and new technologies related to environmental improvement are also topics relevant to global warming, so it is no surprise that “science” occurred more frequently than the reference text, as in “This is literally ‘tossing a snowball on the senate floor to show there’s no global warming’ – 2020 edition. Their ignorance of science and how virulence works is astounding.”

In conclusion, from the word shift graph, it is can be seen that factual statements and doubt of the existence of global warming contribute to the two main negative parts of the discussion, while the search for solutions to global warming contributes the main positive parts.

After comparing the general data, the following part focuses on two events corresponding to two of the lowest points according to Hedonometer analysis, i.e., the hottest recorded temperature in Antarctica in February 2020 and Hurricane Laura in August 2020. As mentioned earlier, extreme weather events and disasters have a high probability of arousing social attention and fuel discussion over global warming. Thus, an analysis of the two events helps provide a deeper understanding of the link between global warming and public opinions.

On February 6, 2020, the temperature in Antarctica reached its highest recorded value of 18.3 °C, which was beaten by a new high of 20.75 °C three days later. The two records breaking in such a short time fuelled a discussion of global warming. The Hedonometer analysis shows that February 9, 2020, was one of the saddest days in the global warming discussion with a score of only 5.48, followed by February 7 with a score of 5.49. In order to know how the happiness shift happened over this topic, data on global warming (3,138 tweets with 63,638 words) from February 6 to 9, 2020, were collected as the comparison text, and a random selection of unfiltered tweets (3,000 tweets with 60,095 words) during the same period as the reference text. Figure 3 (b) shows that a decrease in the positive word “life” ( $h_{avg} = 7.32$ ) and an increase in many negative words such as “threat” ( $h_{avg} = 2.36$ ), “emergency” ( $h_{avg} = 3.06$ ), “death” ( $h_{avg} = 1.54$ ), “disaster” ( $h_{avg} = 1.96$ ), “blame” ( $h_{avg} = 2.82$ ), and “broke” ( $h_{avg} = 2.54$ ) contribute to the decrease of happiness during the four days. Furthermore, the usage of profanity such as “damn” ( $h_{avg} = 2.98$ ), and “idiot” ( $h_{avg} = 3.06$ ) increases, is also responsible for the reduction in happiness level. It is can be inferred from the higher frequency of the words that the public focuses on the reasons causing it, the blame of human behaviours, debate over the authenticity of global warming and the solution to it.

Figure 3 (c) shows the word shift graph for the event of hurricane Laura on August 27, 2020. Two days’ data (1,241 tweets with 3580 words) from August 27 to 28, 2020, were collected as the comparison text, and a random 1,000 tweets with 3015 words during the same time as the reference text. The result shows that the decrease of happiness score is mainly attributable to the negative words “hurricane” ( $h_{avg} = 2.54$ ) and “disaster” ( $h_{avg} = 1.96$ ), which suggests that the hurricane is the main topic during the two days. Pleasant words like “love”, “happy” ( $h_{avg} = 8.3$ ), and “haha” are reduced, which is not difficult to understand -- disaster has no connection with these words. Some fact reporting words like “flood” ( $h_{avg} = 2.42$ ), “death”, “killed” ( $h_{avg} = 1.56$ ), “destruction” ( $h_{avg} = 2.26$ ), and “suffer” ( $h_{avg} = 2.08$ ) show an increased usage, also contributing to the dip of the happiness.

In sum, the Hedonometer analysis showed that the overall attitudes were negative during the 16 months. Extreme weather events and disasters, remarkably, led to a low happiness score. In terms of specific word analysis, the negativeness resulted from both more negative words and less positive words used in the discussion over global warming. The first task of the proposed framework thus far was complete. The more specific linguistic details rest upon Appraisal analysis.

## • Appraisal Analysis

Five hundred random tweets containing “global warming” with 1661 words were analysed in the framework of Appraisal Theory. The annotation focused on the Attitude system (Affect, Judgement and Appreciation) and polarity (negative and positive). The frequencies of occurrence of each parameter were calculated, (they are referred to as frequency here), to explore the frequency and distribution of Attitude.

Table 1. Tests of between-subjects effects

Dependent Variable: Frequency								
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power <sup>b</sup>
Corrected Model	3657.376 <sup>a</sup>	5	731.475	1555.543	.012	.722	7777.716	1.000
Intercept	4050.732	1	4050.732	8614.220	.000	.742	8614.220	1.000
POLARITY	1291.008	1	1291.008	2745.436	.001	.478	2745.436	1.000
ATTITUDE	1840.904	2	920.452	1957.418	.000	.567	3914.836	1.000
POLARITY * ATTITUDE	525.464	2	262.732	158.722	.054	.272	1117.443	1.000
Error	1407.892	2994	.470					
Total	9116.000	3000						
Corrected Total	5065.268	2999						
a. R Squared = .722 (Adjusted R Squared = .722)								
b. Computed using alpha = .05								

A two-way analysis of variance (ANOVA) was conducted to complete the first step using frequencies of these parameters as the dependent variable and Attitude system (Affect, Appreciation and Judgement) and polarity (negative and positive) as the two independent variables. The result (Table 1) shows that the main effects for Attitude ( $F(2, 2994) = 1957.4, p < .001, \eta^2 p = .567$ ) and for polarity ( $F(1, 2994) = 2745.4, p = .001, \eta^2 p = .478$ ) are statistically significant; however, the interaction effect ( $F(1, 2994) = 158.7, p = .054, \eta^2 p = .272$ ) is not. That means the frequencies of Affect, Judgment and Appreciation are significantly different from each other, and the polarity also differ significantly in terms of frequency.

Post-hoc comparisons using the Tukey HSD test suggests that the frequency of Affect ( $M = 0.11, SD = 0.35$ ) is significantly different from Appreciation ( $M = 1.98, SD = 1.3$ ),  $p < .001$ , and from Judgement ( $M = 1.4, SD = 1.19$ ),  $p < .001$ . Similarly, the frequency of Appreciation is also significantly different from Judgement,  $p = .001$ .

Table 2. Multiple comparisons

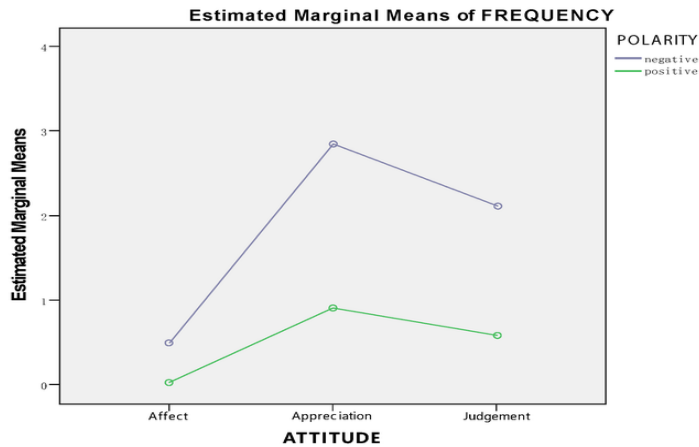
Dependent Variable: Frequency						
Tukey HSD						
(I) ATTITUDE	(J) ATTITUDE	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Affect	Appreciation	-1.87*	.031	.000	-1.95	-1.80
	Judgement	-1.29*	.031	.000	-1.37	-1.22
Appreciation	Affect	1.87*	.031	.000	1.80	1.95
	Judgement	.58*	.031	.001	.51	.65
Judgement	Affect	1.29*	.031	.000	1.22	1.37
	Appreciation	-.58*	.031	.001	-.65	-.51
Based on observed means. The error term is Mean Square (Error) = .470.						
*. The mean difference is significant at the .05 level						

In order to further study how the differences distributed among these parameters, post-hoc Bonferroni pairwise comparisons were conducted. The results show the following significant differences. In terms of polarity, the frequency of negative Affect is significantly lower than Appreciation ( $MD = -2.86$ , 95%  $CI [-2.964, -2.756]$ ),  $p < .001$ , and lower than negative Judgement ( $MD = -2.03$ , 95%  $CI [-2.134, -1.926]$ ),  $p < .001$ . However, negative Appreciation occurs much more frequently than negative Judgement ( $MD = .83$ , 95%  $CI [.726, .934]$ ),  $p = .003$ . The frequency of positive Affect is significantly less than Appreciation ( $MD = -.888$ , 95%  $CI [-.992, -.784]$ ),  $p < .001$ , and less than Judgement ( $MD = -.558$ , 95%  $CI [-.662, -.454]$ ),  $p < .001$ . The frequency of positive Appreciation is significantly higher than Judgement ( $MD = .330$ , 95%  $CI [.226, .434]$ ),  $p = 0.24$ . In summary, in terms of negativity, Affect has the lowest frequency, followed by Judgement and then Appreciation; in terms of positivity, Appreciation has the highest frequency, followed by Judgement and Affect.

With regard to Attitude, Affect shows a significant difference between negativity and positivity,  $p < .001$ , and negative Affect is higher than positive Affect ( $MD = 1.64$ , 95%  $CI [.079, .249]$ ). Appreciation also shows a significant difference between negative Appreciation and positive Appreciation,  $p < .001$ , and the negative aspect has a higher frequency than the positive aspect ( $MD = 2.136$ , 95%  $CI [2.051, 2.221]$ ). Again, Judgement reaches a significant difference between negativity and positivity,  $p = .011$ , and negative Judgement is higher than positive ( $MD = 1.636$ , 95%  $CI [1.551, 1.721]$ ). The results show that negative opinions concerning global warming are expressed more often than positive ones during the time under consideration, which explains the relatively low happiness level calculated by Hedonometer.

Figure 4 shows a more direct view of the frequency and distribution of Affect, Judgement and Appreciation in terms of polarity. Firstly, regarding the three sub-types in Attitude, Affect, surprisingly, has the lowest occurrence in opinion expression, while Appreciation occurs most often, followed by Judgement. In other words, the masses prefer to use the linguistic pattern “something/someone is X” from a third-person perspective to express their attitudes rather than show direct feelings via linguistic patten such as “I love/hate/loathe X”, which involves more personal emotions. However, such a low frequency of direct emotions does not mean a rare relatedness of oneself to global warming. Interestingly, the data show that the number of the first-person pronouns (I and we) ranks second with a ratio of 39.7%, behind the third-person perspective with 42.3%, and the second-person with 18%. The tweets data show that net citizens involve greatly their personal experience, expressed through

Figure 4. General view of Attitude and polarity



“I” or “we”, which is not directly related to the Attitude. For example, in the tweet, “Global warming is a hoax. It’s been beyond freezing nowadays. Like, I don’t remember winter being this cold”, the “Global warming is a hoax” belongs to the Judgement from a third-person perspective. However, the last sentence, “I don’t remember winter being this cold”, is barely associated with any category of Attitude, though it is in a way expressing an attitude. The same is true here where only “warning” pertains to the Judgment evaluation: “Yes, I’ve heard of global warming or warning or whatever, but all I’m saying is I can’t do without my daily Lush baths.” The personal experience being involved but not directly related to the evaluation discussed here accounts for this phenomenon. Simply put, distribution and frequency of Attitude are related to the different perspectives shown by the personal pronouns. However, statistically they are not necessarily in a positive or negative correlation.

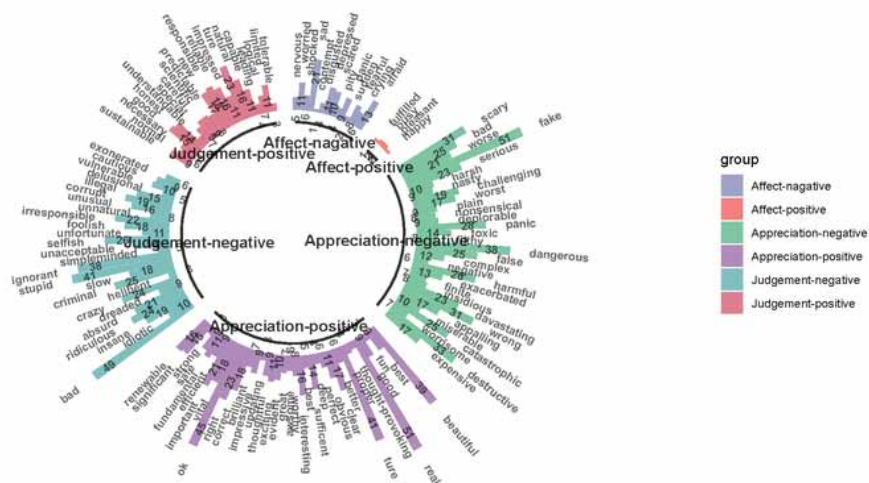
The use of different personal pronouns in written or spoken discourse shows a very different perception of the role of oneself and the distance between oneself and the issue under discussion (Kuo, 1999). The first-person perspective has been interpreted from many perspectives, one of which is the social-psychological perspective that considers it a social phenomenon of self-awareness revealing the position of oneself in social relations to others, usually involving personal experience). The third-person perspective suggests a relatively long distance and external position from the scene with objectivity probably denoted. The statistics indicate that most twitters perhaps, evaluate global warming as observers from external perspective, like the tweet, “Yep, global warming - hopefully people will take it more seriously”. There is also a large group of individuals who start a point of view from themselves with more self-consciousness, typically starting with a first-person singular pronoun, which is not very surprising considering the positive correlation between social media and self-conscious emotions involving more first-person singular pronouns (Buffardi & Campbell, 2008).

Returning to the three categories (Affect, Appreciation, Judgement), the results show that Twitter users tend to evaluate things through Appreciation, such as global warming itself (e.g., “global warming is *real*.” “Global warming is *fake news* and a *hoax*.”), ideas (e.g., “The economic costs of zero carbon targets are absolutely *enormous*. It is *absurd* for the developed world to cripple itself with such targets without *incontrovertible* evidence that it will stop, or reverse global warming. The idea that humans can control climate is *delusional*.”), nature (e.g., “Fires in Australia, *catastrophic* ice cap melt and glaciers retreating. Weather systems do change over time, but climate experts (you’ll be a fan I’m sure) consistently point to the human impact on global warming, the principal driver.”), environment-related policy (e.g., “This is why the right politics have a *hard* time addressing global warming. It’s totally *disruptive* & requires *urgent bold courageous* action.”), and evaluate human

behaviours through Judgement (e.g., “How many ‘world ending’ hysteria does it take to realise *stupid people* are in love with BS panics.”), with few direct emotions conveyed by Affect, such as, “The fact that a virus causes more *panic* than global warming makes me terribly *worried*.” It is easy to observe from the above examples that adjectives play a central role in evaluation. As Pang and Lee (2008) put it, predominately, evaluative language resides in adjectives. Besides, the linguistic pattern types in evaluation concluded by Hunston and Sinclair (2000) and by Bednarek (2009) all contained adjectives. Since “adjectives tend to carry a large proportion of the evaluative load in language” (Taboada et al., 2017, p. 64), some adjectives with relatively high frequency are necessarily listed here (Figure 5).

Differing from the categorisation of the evaluational adjectives into five types according to different properties, i.e. “First-person thought-plus-affect”, “Experiential with bodily reaction”, “Lasting impact”, and “Cognitive evaluation” (Goddard et al., 2019), these adjectives are classified into six categories according to the sub-types of Attitude and their polarities. The variety (type) and number of negative adjectives are much greater than those of the positive adjectives, as can be seen in Figure 5. Notice that the negation of positive adjectives, such as “not ok” and “not good”, which occupy a large part of the data analysed, is not included. Only lexical and contextual positive adjectives are listed here. Suppose all positive adjectives (token) are counted without considering contextuality. In that case, it is found that positive words have a much higher frequency (61%) than negative words (39%). This coincides with the Pollyanna hypothesis (Boucher & Osgood, 1969), which states that positive words are more frequently used than negative words. This can be explained from different perspectives: psychologically, most people tend to look at the bright side (Rozin & Royzman, 2001); morphologically, more positive words exist in languages, and negative words are often derived from positive ones (“unhappy” from “happy”), rather than vice versa (“selfish” from “unselfish”) (Taboada et al., 2017); syntactically, many language users are believed to prefer the “indirect expressions” strategy, that is, the negation of positive words (Aithal & Tan, 2021), such as “not sufficient”.

**Figure 5. Adjectives with relatively high frequency**



However, the highly context-dependent Appraisal analysis results show that the negative expressions are significantly more than positive expressions in the discussion of global warming, which is also the second information given by Figure 4. It shows a tendency that twitters pay more attention to the negative part than the positive part, especially negative topics like global warming.

This is typical negativity bias that human attention is cognitively and selectively directed towards negative information due to the “contagiousness” of negative events (Rozin & Royzman, 2001). The results confirm the phenomenon, just as other empirical evidence previously did.

Briefly, Appraisal analysis at the micro-level yielded the following elaborate linguistic results: in terms of the Attitude axis, Twitter users preferred to evaluate things related to global warming and evaluate people’s behaviours, rather than directly express their emotions by saying things like “I’m angry about it”. In terms of part of speech, adjectives were the most frequently used in expressing attitude. In terms of polarity, negative opinions outnumbered positive ones, which is a quintessential negative bias. The results of the Appraisal analysis were in line with the Hedonometer results.

This study started from the big picture and narrowed to a particular consideration, integrating the advantages of Hedonometer and Appraisal analysis to construct a systematic framework. Via this framework, the research assessed public attitude towards global warming during a 16-month period and how they conveyed their attitudes linguistically.

## CONCLUSION

The current study presented a new framework, viz. the combination of Hedonometer and Appraisal Theory, to analyse Twitter users’ attitudes towards global warming on Twitter. As an NLP technique, Hedonometer helps in the examination of the general polarity, which is very laborious if manually handled, while Appraisal Theory (only Attitude is analysed here, but Graduation and Engagement can also be analysed) deals with specific linguistic realisation and linguistic features in the corpus. In the age of big data, this framework facilitates data-processing in discourse analysis. From a methodological point of view, this study is repeatable and reliable. Considering the contextuality of Appraisal Theory, a sample study is employed. Generally speaking, the framework is a combination of generality and minutia, result and explanation, new technique and traditional method.

In the Hedonometer analysis, the corpus consisted of 495,231 tweets containing the words “global warming” with more than 20 million words posted from January 1, 2020, to April 30, 2021. The results showed that the happiness score of tweets containing the words “global warming” was consistently lower than the overall happiness score of all tweets in the same period. Therefore, to find out what specific words contribute to this lower level, a comparison study was carried out with 10,000 random tweets each month (from January 1, 2020, to April 30, 2021) as the comparison text, and the collected date as the reference text.

The word shift graph showed a happiness score of 5.98 for the reference text, and 5.72 for the comparison text. This is because negative words like “pollution”, “damage”, “disaster”, “killing”, “death”, “tragedy” and some profanity like “shit” escalated while positive words like “love”, “lol”, “haha” dropped. From the words listed in the word shift graph, it was discovered that the tweets concerning the dispute over whether global warming is real contributed to the negative opinion, and finding the solutions to global warming contributed to the positive. The study focused on two events that would probably spark a discussion over global warming: the hottest record in Antarctica in February 2020 and Hurricane Laura in August 2020. The results displayed a very low happiness score, with more negative words and fewer positive words.

The Appraisal analysis centred around Attitude involving three sub-types, viz. Affect, Judgement and Appreciation and two polarities, positive and negative. A random 500 tweets were manually annotated. The overall frequency and distribution results showed that Affect had the lowest frequency while Appreciation had the highest frequency, followed by Judgement. Twitter users tended to express their opinions on global warming through Appreciation (evaluating things), and Judgement (evaluating people’s behaviours), rather than directly expressing their emotions through Affect. As Cavasso and Taboada (2021) put it, “strong emotional content is couched in terms of Judgement and Appreciation” (p. 27). Put another way, the results suggested that language users produce sentences like “Global warming is real/disaster” or “It’s crazy that ignorant people just don’t believe in global

warming” rather than “I’m angry/worried about global warming”. In line with the Hedonometer results, twitters used more negative expressions than positive expressions in every category (Affect, Judgement and Appreciation). More specifically, the social media users directly express emotions like anger, worry, fear, and sadness rather than joy or happiness, and criticised more than praised in the global warming discussion.

Apart from the distribution and frequency, two related phenomena were also discussed, i.e., the relation between the person and the sub-types, and positive versus negative bias. The higher frequency of Appreciation and Judgement showed a tendency toward third-person perspective. However, the low rate of Affect was not correlated with the low rate of first-person perspective. The first-person perspective was often taken in tweet discourse, usually by linking personal experience with the topic under discussion. The overall negative opinions towards global warming confirmed the negative asymmetry phenomenon where people express more negativity than positivity towards negative events that more easily draw attention and produce “larger, more consistent, more multifaceted, or more lasting effects” (Jing-Schmidt, 2007, p. 418) than positive events.

In summation, the present study found that the tweets pertaining to global warming were generally negative and expressed mostly by Appreciation with Judgement following and with Affect occurring least. In most circumstances, twitters expressed their opinions from a third-person perspective which is an external perspective. There are still many occasions where they used the first-person perspective by linking personal experience with global warming.

The study shed light on how the public viewed global warming, providing new literature for global warming studies. Moreover, the new framework proposed here, which combines both advantages of NLP and the traditional method, offers more possibility for uncovering information on attitudes, especially from a large corpus.

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## ENDNOTE

- <sup>1</sup> The right part indicates words contributing to the increase in happiness score in the global warming tweets, the left part indicates words contributing to the decrease in happiness score in the global warming. Yellow bar means a word above average happiness level (positive word), blue bar means a word below average happiness level (negative word). + means positive, - means negative. indicates an increased usage of a word in comparison text, - indicates a decreased usage of a word in comparison text. For example, + means an increase in positive words in comparison text, - means an increase in positive words, - means a decrease in negative words, + means a decrease in positive words.

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