

# Have media texts become more humorous? A diachronic analysis of the Corpus of Historical American English

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## Abstract

*As a research topic, humour has drawn much attention from multiple disciplines including linguistics. Based on Engelthaler & Hills' (2018) humour scale, this study developed a measure named Humour Index (HMI) to quantify the degree of humour of texts. This measure was applied to examine the diachronic changes in the degree of humour of American newspapers and magazines across a time span of 118 years (1900-2017) with the use of texts from Corpus of Historical American English (COHA). Besides, the study also discussed the contributions of different types of words to the degree of humour in the two genres. The results show significant uptrends in the degree of humour of both newspapers and magazines in the examined period. Moreover, derogatory and offensive words are found to be less frequently used than other categories of words in both genres. This study provides both theoretical and methodological implications for humour studies and claims or hypotheses of previous research, such as infotainment and linguistic positivity bias.*

*Keywords: humour, quantitative linguistics, diachronic linguistics.*

## 1. Introduction

Humour is a ubiquitous phenomenon in human activities (Martin, 2007). It has been defined as a term with multiple meanings (Moran, 2002). Cognitively, humour can be regarded as both a stimulus and a response to the stimulus (e.g., laughter), or a personality trait and a capability to produce such a response. From a sociological perspective, it is related to sophisticated interactions (e.g., mocking or teasing) between individuals (Moran, 2002). Humour is believed to have plentiful benefits (Kuipers, 2005). It is able to soothe pain, bring comfort (Strick, 2021),

dissolve negative emotions (Miczo, 2021; Strick et al., 2009), elicit positive emotions (Zekavat, 2021), increase the persuasiveness of information (Zekavat, 2021), and strengthen social cohesion (Alexander, 1986; Keltner et al., 2001; Miczo, 2021). With these diverse meanings and functions, humour has been an issue of interdisciplinary interest. Humour as a research topic has received attention from many disciplines, such as psychology (Decker & Rotondo, 1999; Cann & Matson, 2014; Wu et al., 2021), sociology (Meyer et al., 2017; Richman, 1995; Şahin 2021; Tsai et al., 2019), education (Booth-Butterfield & Wanzer, 2016; Tsukawaki & Imura, 2020, 2022) and anthropology (Hunt, 1993; Yue et al., 2014).

The topic of humour has also appealed to linguists during the past decades. Linguists have proposed humour-related linguistic theories (Martin, 2007; Raskin, 1985) or conducted linguistics-based empirical studies on humour (Calhoun, 2019; Gibbs et al., 2014; Tsakona, 2009). The majority of such studies rely on manual analysis and are qualitative in nature, and thus may be affected by the subjectivity of researchers. Hence, such qualitative studies may be well complemented by quantitative approaches and computational humour research (Faraj & Abdullah, 2021; Reyes et al., 2009; Zhang & Liu, 2014). Recent computational humour studies, particularly in humour recognition, have employed machine learning models but often lead to results that are difficult to interpret. In comparison, the application of the bag-of-words approach in humour research may help yield straightforward and interpretable results. In addition, most previous studies are synchronic in nature while little research has examined the diachronic change of humour in texts.

Therefore, the present study developed a measure based on the bag-of-words model to quantify the degree of humour in texts. Using a large dataset of American magazines and newspapers, we aimed to present the diachronic trend in the degree of humour in American media texts from the 1900s to the 2010s. Moreover, this study also investigated the weight of different categories of words related to humour in each decade.

## **2. Literature review**

### **2.1. Humour as a research topic in linguistic studies**

In linguistics, the research of humour is well established. Theoretically, linguists have developed a bunch of linguistic theories of humour. The Semantic Script Theory of Humour (SSTH) (Raskin, 1985) is perhaps the most mature and widely used among these theories (Martin, 2007). According to the SSTH, there is an obvious script and an underlying script in a joke; these two scripts must be incongruous and also overlapping in meaning. The set-up of the joke elicits the obvious script, while the punchline of the joke switches the interpretation (i.e., the obvious script) to the underlying script (Labutov & Lipson, 2012; Raskin, 1985). That is, the perception of humour is largely dependent on the subversion of the previous interpretation.

Expanding on the SSTH, Attardo & Raskin (1991) formulated a new theory termed the General Theory of Verbal Humour (GTVH). GTVH retains the idea of the two scripts, and also introduces other parameters which may compose humour, including the target, the narrative strategy, the situation, and the language (Attardo & Raskin, 1991). Among these parameters, the language parameter consists of phonological choices, lexical choices, syntactic choices, etc. As such, it would be important to study humour from the perspective of different linguistic units, for instance, the lexis.

With the guidance of linguistic theories of humour, linguistics-based empirical studies on humour mainly aim to probe into humour-related elements in language and texts. Such humour research has been conducted on various types of discourse. Some researchers have investigated humour in formal discourse (Takovski, 2019; Tsakona, 2009; Urbatsch, 2022) as well as daily

conversations (Gibbs et al., 2014; Hay, 2001; Priego-Valverde, 2021). In addition, multimodal discourse has also been employed as linguistic data for humour research (Breazu & Machin, 2022; Calhoun, 2019). In such studies, commonly-used research methods include conversation analysis, discourse analysis, content analysis, interviews, etc. For example, Priego-Valverde (2021) employed conversation analysis to examine failed humorous instances in French conversations. After the annotation of the audio signal and the humorous items, the researcher analysed in detail each utterance that satisfies the criteria from the frame, the target, the turn-taking, etc. The results showed that disalignment (i.e., disrupting the speaker's ongoing narration) and disaffiliation (i.e., producing humour in a serious atmosphere and vice versa) were identified as two factors of interactional failure. Calhoun (2019) carried out a multimodal discourse analysis to find out semiotic features of an anti-hegemonic racial comedy in the works of the most-followed person on *Vine*, a short-form video-sharing platform. Takovski (2019) combined content analysis and interviews to discuss the role of humour in a social movement and concluded that humour prompted free expression and engagement in the movement.

The studies reviewed thus far mostly employed qualitative methods to analyse the features and functions of humour in various discourse types. Their findings have deepened the understanding of the use of humour in various contexts, and also show that humour is a topic worthy of further exploration in linguistic research. However, most studies in this line rely on manual analysis and are qualitative in nature. Thus, such studies may be affected by the subjectivity of scholars and the limited sample size. In this sense, evidence-based empirical studies that adopted quantitative methods may serve to complement the conventional approaches.

## **2.2. The application of computational approaches to humour recognition**

Perhaps motivated by the advantages of quantitative methods, a number of researchers began to introduce computational approaches into humour research, which opened up a new field of research called computational humour (Amin & Burghardt, 2020; Reyes et al., 2009; Zhang & Liu, 2014). There are two main research lines in the field, namely humour generation and humour recognition. Early works in computational humour predominantly focused on humour generation, i.e., using natural language processing tools to imitate human humour and automatically generate humorous texts such as jokes, puns, etc. (Binsted & Ritchie, 1994; Hong & Ong, 2009; Yu et al., 2018). Humour recognition deals with the detection of humour in different linguistic units (Meaney et al., 2021; Mihalcea & Pulman, 2007; Taylor & Mazlack, 2004; Yang et al., 2015). Compared with humour generation, humour recognition is arguably harder to achieve, since it is impossible for algorithms or models to recognise all types of humour. However, with the progress of techniques, humour recognition has also gained much more attention in recent decades and achieved higher accuracy.

Taylor & Mazlack's (2004) work is perhaps the first theory-based attempt at computational humour recognition. Their research target is Knock Knock jokes, a type of verbally expressed humour with a restricted pattern. Based on the SSTH (Raskin, 1985), Taylor & Mazlack (2004) designed a joke recogniser. They fed Knock Knock jokes with wordplay features first into the recogniser and then used it to distinguish such jokes from their non-humorous counterparts on the basis of N-grams. The results showed that the recogniser was successful in recognising wordplay in most jokes and also in discarding texts that are not jokes. However, partly due to the modest size of the N-gram dataset, it failed in detecting most punchlines in jokes.

Following Taylor & Mazlack (2004), a number of researchers have treated computational humour recognition as a binary classification task (Buscaldi & Rosso, 2007; Mihalcea & Pulman, 2007; Mihalcea & Strapparava, 2005, 2006). That is, the major goal of such tasks is to differentiate humorous texts from non-humorous texts. Moreover, most studies in this line of

research follow the rule of training a model with certain linguistic features related to humour, which has become the mainstream of the field. For example, Mihalcea & Strapparava (2005) experimented with a machine learning tool using three stylistic features (*alliteration*, *antonymy*, and *adult slang*) and content-based features to identify short humorous sentences called one-liners. The results revealed that such a computational tool based on the above features had good performance in the classification task, which further provided a viable approach for humour identification.

Nonetheless, Zhang & Liu (2014) noted that, in previous studies of humour recognition, there was a lack of systematic investigation of features that trigger humour, and that most of the linguistic instances studied were static. To address these issues, Zhang & Liu (2014) derived humour-inducing features from humour theories, linguistic norms, and affective dimensions, and focused on fresh and dynamic data consisting of tweets. They chose a classification algorithm called Gradient Boosted Regression Trees (Friedman, 2002) to build their model and achieved high accuracy in the classification task. Likewise, Yang et al. (2015) also explored several features behind humour from related theories to recognise humour with computational approaches.

Some researchers attempted to treat humour recognition as a ranking task (Potash et al., 2016; Radev et al., 2016; Shahaf et al., 2015). In other words, they tried to achieve humour recognition by determining which text is funnier than its counterparts. For instance, Shahaf et al. (2015) trained a random forest classifier aiming to pick the funnier cartoon caption in a pair by extracting a set of features. The results showed that funnier captions tended to have a simpler grammatical structure, less use of proper nouns, and shorter phrases. In a similar study aiming at predicting the funnier cartoon caption, Radev et al. (2016) compared several automatic methods for the ranking task. It was found that negative sentiment, human-centredness, and lexical centrality could be used as predictors for funnier captions.

More recently, researchers started to address a more challenging issue, which is to automatically predict humour scores (Faraj & Abdullah, 2021; Ortiz-Bejar et al., 2018; Pang et al., 2021) instead of regarding humour recognition as a binary classification task. Ortiz-Bejar et al. (2018) participated in *Humour Analysis based on Human Annotation* (HAHA) task on IberEval 2018 (Castro et al., 2018) to complete a humour classification task and a task for humour score prediction. To predict humour scores, they trained a Kernel Ridge regression model with a set of human-labelled Twitter data provided by the HAHA task. This model yielded the best performance in the prediction task with the lowest root mean squared error. Pang et al. (2021) predicted humour ratings in another workshop, SemEval 2021 (Meaney et al., 2021). They applied and adjusted various unsupervised language models that were pre-trained on unlabelled data, and then adapted these models. The results showed that ERNIE (Enhance representation through knowledge integration) 2.0 (Sun et al., 2020) performed best in the rating task.

Overall, these computational humour studies have shown the value of quantitative methods in humour research. Such methods have taken humour research to a more sophisticated level and continuously expand the outreach of this field. However, such complicated machine learning approaches often lead to the problem of interpretability. That is, it may be difficult to interpret what the predictions are based on and to diagnose problems if the models go wrong. Consequently, it may not be reliable to completely depend on these models. As such, the present study resorts to a computational method easier to interpret to quantify humour in texts, that is, with a bag-of-words approach.

A bag-of-words model usually treats a text as a set of unordered words (Jiang et al., 2020; Pham, 2022). It represents texts by examining occurrences of a list of words (Pham, 2022). A number of studies on sentiment analysis have used the bag-of-words approach and achieved desired efficacy (Alkan et al., 2022; Lu & Wu, 2019; Park & Kim, 2016). It is typical of such

dictionary-based sentiment analysis to judge whether a text evokes positivity or negativity in light of word matching and the polarity of words (Wilson et al., 2005). Some humour studies have also validated the predictive power of bag-of-words in computational humour recognition (Buscaldi & Rosso, 2007; Yang et al., 2015; Zhang & Liu, 2014). Buscaldi & Rosso (2007) found that, among the examined classifiers, the highest accuracy was achieved by the classifier with bag-of-words as features. Yang et al. (2015) confirmed that bag-of-words had acceptable accuracy and precision in humour recognition. In addition, as mentioned before, GTVH (Attardo & Raskin, 1991) has confirmed the significance of lexical choices in humour. Thus, we believe that a bag-of-words model is able to represent the degree of humour at least to some extent. To achieve this goal, the study chooses the dataset of Engelthaler & Hills (2018) as the basis of our bag-of-words model to assess the humour ratings of texts.

Engelthaler & Hills (2018) first sampled 4,997 commonly-used English words from the intersection of various norms, such as valence, arousal, and dominance norms (Warriner et al., 2013), age of acquisition norms (Kuperman et al., 2012), etc. Afterward, 950 participants were recruited to rate these words on a scale from 1 (unfunny or dull) to 5 (funny or associated with humorous thought or language). Hence, the higher the rating, the more humorous the word is perceived. These participants were given a list of 211 words to rate. Among the words, 11 were calibrator words to show the range of the humour scale and increase the reliability of subsequent rating. The rest 200 words were randomly sampled from the original list of 4,997 words, and the sample was different for each participant. Since words to be rated were given out of context, participants had to rate with their previous knowledge and their current feelings when they saw the words. The final humour rating of a word is the mean value of all ratings from participants. Their work may be the first attempt to quantify lexical humour, which allows researchers to further investigate humour quantitatively in language and texts. Meanwhile, it should be acknowledged that there remain some possible limitations in Engelthaler & Hills' (2018) research design. On the one hand, as mentioned earlier, words given to participants were out of context. In fact, the context plays an important role in humour perception. Seemingly funny words may generate jokes in some contexts, but may appear humourless in other contexts. On the other hand, the guidelines of the humour scale presented to participants were not disambiguated. Dullness is not the same with unfunniness, and funniness is not totally equal to humorous thoughts or language such as absurdity. However, this limitation appears difficult to avoid because humour does not have a clear-cut boundary. Although the drawbacks may influence the results of subsequent research, we believe that Engelthaler & Hills (2018) have successfully provided a dataset which presents humour in miniature due to its acceptable reliability, and therefore it is able to be used as the basis for judging humour.

Building on Engelthaler & Hills (2018), Westbury & Hollis (2018) conducted a further study on the humour norms. They analysed four elements (*semantics, phonology, orthography, frequency*) that might be correlated with their perceived degree of humour. It is noteworthy that in the exploration of semantic factors, six semantic categories (*party, sex, insults, profanity, body function, animals*) were identified (the definitions of each category are introduced in Section 3.3.4). This categorisation was completed by using vectors from the word2vec model, a technique to measure semantic similarity between words. They started with manually classifying the 200 most humorous words in Engelthaler & Hills' (2018) humour norms into six categories and then created a category-defining vector (CDV) for each category through averaging together word vectors. The close distance between the vector of a word and the CDV of a category denotes their high similarity in semantics, which means that the word is likely to be a member of the category. In order to increase the accuracy, they later sorted the first 100 words that are closest to each CDVs and then defined a final definitive CDV with the sorted words for each category. Taking advantage of the definitive CDVs, the two researchers were capable of categorising more words, and presented the 50 closest words to each definitive CDV

in the appendix. Their study makes it possible to conduct more fine-grained analysis of the humour ratings of words.

To sum up, although researchers have investigated humour-related elements in different linguistic units with various methods, previous studies are mostly synchronic in nature while few have investigated the diachronic change of humour in texts. Two exceptions were Laineste (2016) and Archakis & Tsakona (2021). The former analysed the temporal change of humorous discourse in folklore across three periods. The latter examined online jokes targeting Greek migrants in two periods. However, these two studies only discussed humorous discourse in certain selected time periods, instead of presenting a continuous historical change.

### **2.3. Infotainment: A phenomenon related to the change of humour**

In the media world, an emerging phenomenon related to the change of humour is infotainment (Brants & Neijens, 1998; Delli Carpini & Williams, 2001). Infotainment is the combination of information and entertainment (Boukes, 2019; Otto et al., 2017). It should be noted that infotainment is not a shift in genre but a trend or a process that the style of different media genres is becoming more amusing and funnier to keep audiences interested and engaged (Boukes, 2019; Delli Carpini & Williams, 2001). Humour is one significant component of the infotainment because it helps to intensify the entertaining degree (Davis et al., 2020; Riesch, 2015). Many scholars have detected elements of infotainment in either videos (Davis et al., 2020; Xenos & Becker, 2009) or print media such as newspapers (Bernhard & Scharf, 2008; Jebiril et al., 2013). Nonetheless, the infotainment phenomenon in these studies was also identified through subjective analysis, lacking the support of quantitative data.

In summary, there is a lack of humour studies in linguistics conducted from a diachronic perspective. In light of this possible gap, on the basis of bag-of-words derived from Engelthaler & Hills' (2018) humour rating norms, the present study sets out to quantify the degree of humour of American magazine and newspaper discourse, and explore their changes over time to examine their relationship with infotainment. Furthermore, this study also tries to classify part of words in the humour rating norms according to Westbury & Hollis' (2018) semantic categories so as to find out the preference of American magazines and newspapers for different words related to humour.

## **3. Methodology**

### **3.1. Research questions**

This study sets out to adopt a computational approach to investigate the temporal change in the degree of humour of American magazines and newspapers from the 1900s to the 2010s. To quantify the degree of humour, a measure named Humour Index (HMI) was designed based on the humour ratings of words in the investigated texts (see Section 3.3.1). Three questions are to be addressed:

- (1) From the perspective of genre variation, is there a significant difference in the degree of humour between magazine texts and newspaper texts?
- (2) From the perspective of diachronic change, has the degree of humour changed across time in the two genres? When did the most abrupt change occur (if any)?
- (3) At the lexical level, what types of words in Engelthaler & Hills' (2018) humour norms are preferred in the two genres?

### 3.2. Corpus data

The corpus data used in this study is the Corpus of Historical American English (COHA), which is downloadable at request (<https://www.corpusdata.org/>) and provides texts classified by genre and time. COHA consists of more than 400 million tokens of English texts (including *Fiction*, *Magazine*, *Newspaper* and *Non-fiction genres*) from the 1810s to the 2010s.

We employed the magazine portion and the newspaper portion of COHA as the corpus data for this study. The two genres were selected because they cover everyday events in society, describe people’s real life, and hence would reflect diachronic changes in language use more closely than other genres. It should be noted that COHA provides both raw texts and lemmatised texts. In the present study, we used the lemmatised texts to avoid the influence of morphological changes.

The degree of humour of a text is assessed based on the humour ratings of English words proposed by Engelthaler & Hills (2018). Specific algorithms are introduced in Section 3.3.

### 3.3. Data processing

#### 3.3.1. The calculation of Humour Index

We coded a python script to calculate the HMI values of the examined magazine and newspaper texts by year from 1900 to 2017. The algorithm of HMI calculation is presented in Formula 1 and Formula 2 respectively. For convenience, we refer to the words in Engelthaler & Hills’ (2018) humour norms as *EH-words* in the rest of this paper.

Formula 1

$$HMI(\text{of a text}) = \frac{\sum_{i=1}^n (Freq_i * HR_i)}{\sum_{i=1}^n Freq_i}$$

In Formula 1,  $n$  is the number of EH-word types that occur in the given text,  $Freq_i$  is the raw frequency of the  $i$ th EH-word type in the text, and  $HR_i$  is the humour rating of the  $i$ th EH-word type according to Engelthaler & Hills (2018).

Formula 2

$$HMI(\text{of a year}) = \frac{\sum_{i=1}^N (Freq_i * HR_i)}{\sum_{i=1}^N Freq_i}$$

In Formula 2,  $N$  is the number of EH-word types that occur in all the texts of the given year for the genre,  $Freq_i$  is the raw frequency of the  $i$ th EH-word type in that year for the genre, and  $HR_i$  is the humour rating of the  $i$ th EH-word type according to Engelthaler & Hills (2018).

(1)

He	<i>shepherded</i>	the nomination of Indiana	<i>fruitcake</i>	Daniel Manion
	2.56		3.83	
to	a widely	ridiculed federal judgeship.		

(magazine\_1990\_480979)

We use an exemplar sentence to illustrate how to apply these algorithms (see [1]). EH-words in this example are marked in italic type and their humour ratings are given right beneath the words. Suppose that (1) is the only sentence in a text, then the HMI of the text is computed as:

$$HMI = \frac{2.56 \times 1 + 3.83 \times 1}{1 + 1} = 3.20$$

Specific steps to calculate the HMI of a given corpus are shown in Figure 1. The same procedure was repeated until all the HMI values of these two genres from 1900 to 2017 were calculated.

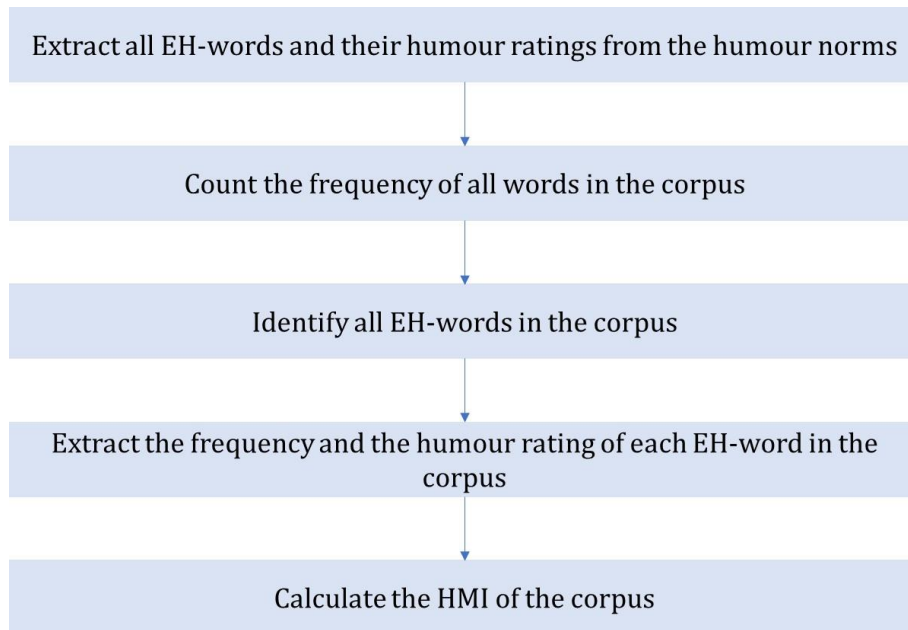


Figure 1. Steps to calculate the HMI of a corpus

### 3.3.2. Trend detection

Trend detection serves to detect whether a time series has a general downward trend or upward trend or no significant trend (Hamed & Rao, 1998). Several statistical tests have been designed for trend detection. The present study used Mann-Kendall test (Hamed, 2008) and Cox-Stuart test (Rutkowska, 2015) to observe whether the language of magazines or newspapers has become more humorous. The results of the two tests were cross-validated to ensure the accuracy. A python script was coded to apply Mann-Kendall test and Cox-Stuart test to the HMI series of magazine texts and that of newspaper texts across the examined years.

### 3.3.3. Change point detection

Change point detection is a technique to identify abrupt changes and can be applied to all types of chronologically ordered data. It can detect the number and the location of change points which mark a sudden change from a stable state to another one (Taylor, 2000). We adopted it to capture any possible jumps in HMI.

A python script was written to serve this purpose. Three methods were covered in the detection, i.e., Pettitt test (Mallakpour & Villarini, 2016), Buishand U test (Habeeb et al., 2021),



and Standard Normal Homogeneity test (SNHT) (Pohlert, 2020). These tests were applied in the two time series of HMI values of magazines and newspapers.

### 3.3.4. Cosine similarity to EH-word categories

In addition to longitudinal changes, it is also of interest to investigate what types of EH-words are preferred in magazines and newspapers during each decade across these 118 years.

We only considered the 100 EH-words that contribute the most to the HMI of each decade. That is, the considered EH-words have the highest humour ratings among all the EH-words that occur in the texts of that decade. Following the logic of Formulas 1 and 2, the calculation of the HMI per decade is presented in Formula 3.

Formula 3

$$HMI(\text{of a decade}) = \frac{\sum_{i=1}^{ND} (Freq_i * HR_i)}{\sum_{i=1}^{ND} Freq_i}$$

In Formula 3, *ND* is the number of EH-word types that occur in all the texts of the given decade for the genre, *Freq<sub>i</sub>* is the raw frequency of the *i*th EH-word type in that decade, and *HR<sub>i</sub>* is the humour rating of the *i*th EH-word type according to Engelthaler & Hills (2018).

The categorisation of EH-words was motivated by Westbury & Hollis (2018). They defined six word categories (*party*, *sex*, *insults*, *profanity*, *body function* and *animals*) based on Engelthaler & Hills' (2018) humour norms. Detailed definitions of these categories are shown in Table 1. Westbury and Hollis also identified the 50 closest words to each category. Definitions and example words in Table 1 are all extracted from Westbury & Hollis (2018).

Table 1. Westbury & Hollis' (2018) six categories of EH-words

Category	Definition	Example
<i>Party</i>	A category that comprises words related with enjoying oneself greatly.	<i>dinner, chitchat</i>
<i>Sex</i>	A category containing sex-related words.	<i>nude, penis</i>
<i>Insults</i>	A category containing insulting words.	<i>idiot, moron</i>
<i>Profanity</i>	A category containing profane terms.	<i>honky, heck</i>
<i>Body function</i>	A category that contains terms concerned with nonsexual bodily functions.	<i>puke, snort</i>
<i>Animals</i>	A category that is composed of words associated with animals, mainly but not exclusively animal names.	<i>monkey, puppy</i>

Since Westbury & Hollis (2018) did not make the definitive CDVs for the categorisation of each category available, we classified the 100 EH-words of each decade based on the 50 closest words to each category provided in their study. For each category, the 50 closest words were regarded as a reference list. Our goal is to measure the semantic similarity between each reference list and each examined EH-word, and then assess the association between each examined EH-word and each category. Here, the semantic similarity is defined by the distance between word vectors, as suggested in Westbury & Hollis (2018). To be specific, the similarity value is computed as the cosine distance of the meaning between two linguistic units (Sitikhu et al., 2019). If words occur in similar contexts, they are assumed to be semantically parallel (Kulkarni et al., 2015). The basic idea of computing semantic similarity is to transform words into multi-dimensional vectors and then measure the cosine of the angle between them (Sitikhu et al., 2019;

Soyusiawaty & Zakaria, 2018). The cosine value determines whether the two vectors point to a similar orientation (Soyusiawaty & Zakaria, 2018). Its value ranges from -1 to 1; the closer it is to 1, the greater the similarity between the two vectors.

In order to calculate the similarity between each reference list and each examined EH-word, we used word-embeddings technique which labels words in a text as a multi-dimensional vector in space (Mikolov et al., 2013). We first converted tokenised texts of each decade into a matrix and then input the matrix into the word-embedding model. After extracting vectors of the examined EH-words and the words in each reference list, we calculated the similarity between each EH-word and each word in the reference list for a particular category. Then, we averaged similarity values of the examined EH-word and all words in the reference list to obtain the final similarity value of the EH-word and the category.

Figure 2 shows the specific steps to calculate the similarity values of each EH-word and the six word categories. The function *cosine\_similarity* in the *Python* module *sklearn* was used to calculate the similarity values.

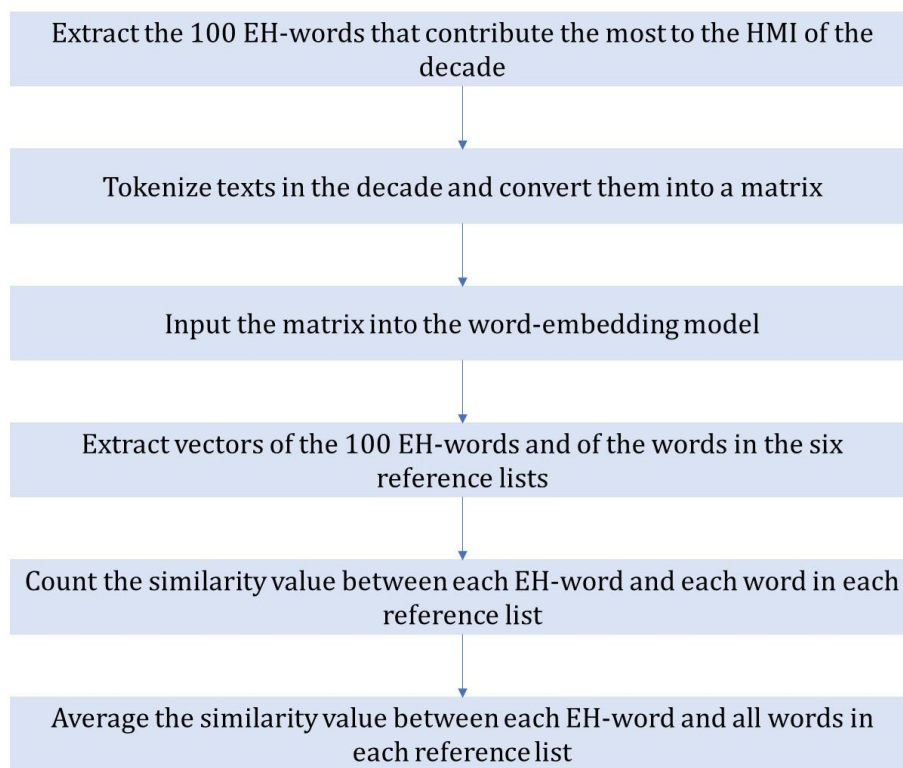


Figure 2. Steps to calculate the similarity values between EH-words and the six categories

In many cases, a word may be related to more than one category (Westbury & Hollis, 2018). For instance, the word *fuck* is one of the 50 closest words to the sex category and also one of the closest to the profanity category. Therefore, it may be inappropriate to simply attribute an EH-word to one single category with which it has the highest cosine similarity. Instead, it is necessary to take into account its similarity to all the categories and thus consider an EH-word as a “hybrid” of several word categories. For each genre in each decade, we added similarity values of the 100 EH-words for each category and obtained six sums of similarity values, which indicate the inclination of the texts towards the use of the six categories of words. These data will be visualised and analysed in Section 3.3.

## 4. Results

### 4.1. Descriptive statistics

The descriptive statistics of the HMI of magazine texts and newspaper texts are presented in Table 2. The results of a paired-sample t-test show that HMI values of magazines are significantly higher than those of newspapers ( $t = 21.968$ ,  $p < .002$ ), which suggests the lexical use of American magazines is more humorous than that of newspapers in the examined period.

Table 2. Descriptive statistics of HMI values of magazines and newspapers

Genre	N (years)	Mean	S.D.
<i>Magazines</i>	118	2.1684	.0096
<i>Newspapers</i>	118	2.1440	.0160

### 4.2. Trends and change points of HMI values

The scatter plots of HMI values of magazine texts and newspaper texts are shown in Figures 3 and 4. As can be seen, HMI values of both genres have increased on the whole with fluctuations in certain periods. For magazines, the results of Mann-Kendall test ( $p < .001$ ) and Cox-Stuart test ( $p < .001$ ) confirm that their HMI values have increased significantly over this period. Likewise, an upward trend in the HMI of newspapers is also identified by Mann-Kendall test ( $p < .001$ ) and Cox-Stuart test ( $p < .001$ ).

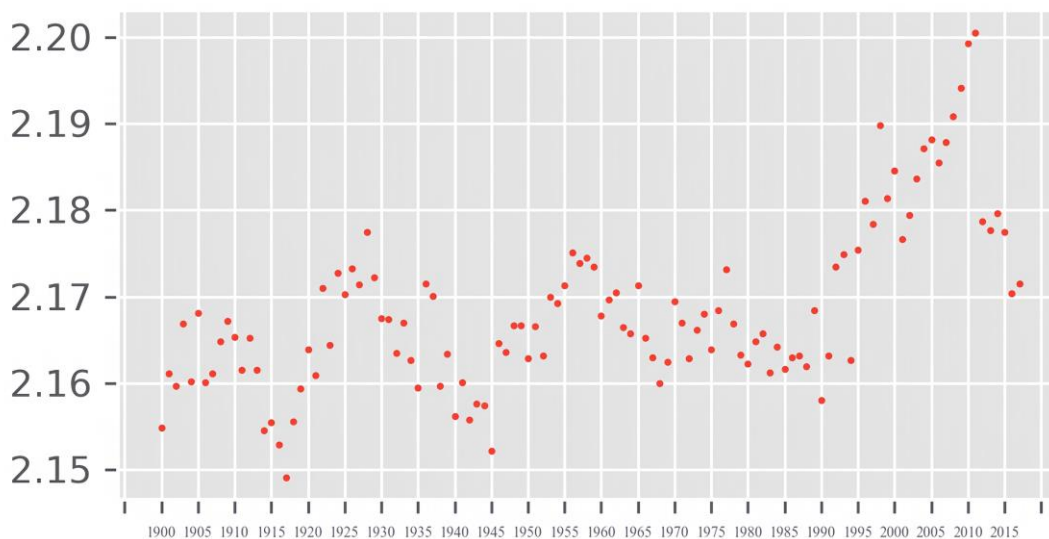


Figure 3. The trend of HMI values of magazines

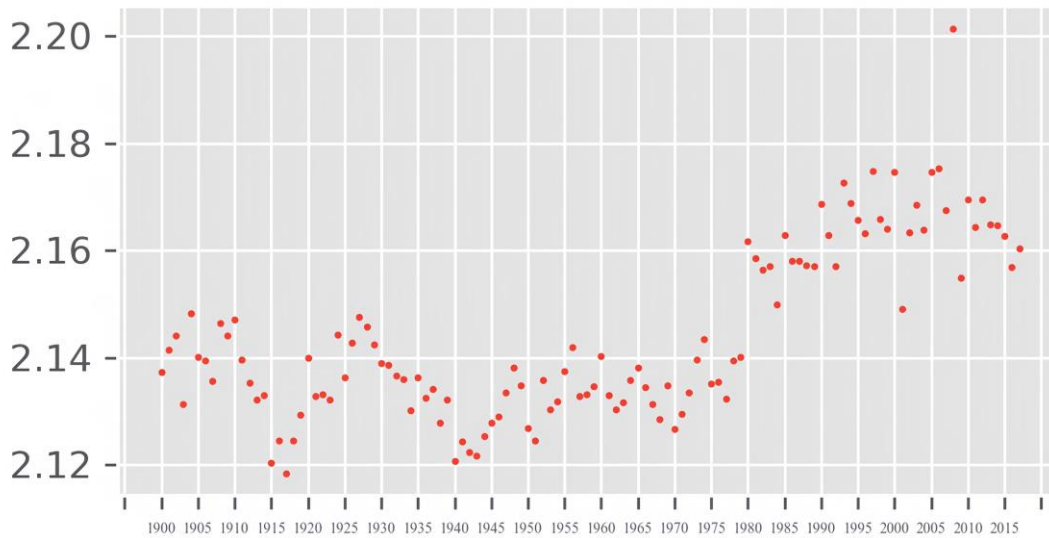


Figure 4. The trend of HMI values of newspapers

From Figure 3, it can also be seen that the HMI values of magazines seem to fluctuate roughly between 2.15 and 2.18 before the 1990s. However, there appears to be a jump to a higher level since the 1990s. The results of three change point tests, as shown in Table 3, help to uncover the change point. The Pettitt test and Buishand U test both recognise 1992 as the change point. The mean values of HMI from 1900 to 1992 and from 1992 to 2017 are calculated respectively, in order to compare the HMI values before and after the change point. As shown in Figure 5, the mean value before 1992 is 2.1646 while that after 1992 is 2.1823, with a significant difference between them ( $t = -9.507, p < .001$ ).

Similar to the trend of magazines, the HMI values of newspapers have fluctuated within a certain range and then experienced an abrupt increase around 1980. The results of change point detection show that the specific time of change for newspapers is indeed different from that of magazines. In Table 4, Buishand U test and SNHT both identify the year 1980 as the change point. Figure 6 shows the mean value before 1980 is 2.1343 while the mean value after 1980 is 2.1645. The latter is also significantly larger than the former ( $t = -19.946, p < .001$ ). The difference between periods before and after the change point of newspapers is even greater than that of magazines.

Table 3. Results of change-point tests concerning magazines

Test	Change point	HMI value
<i>Pettitt</i>	1992	2.1735
<i>Buishand U</i>	1992	2.1735
<i>SNHT</i>	1995	2.1754

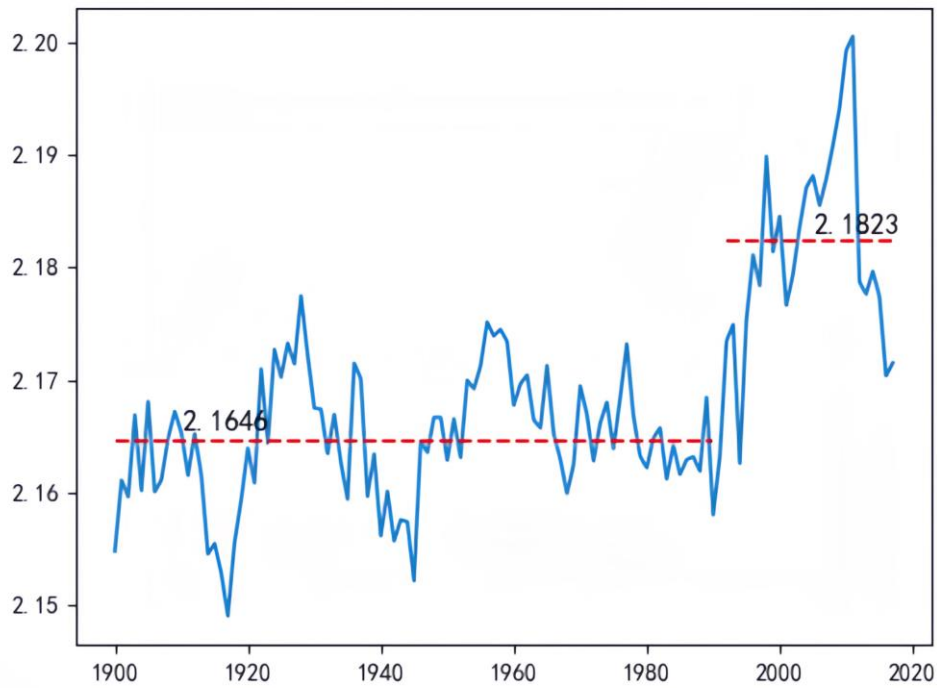


Figure 5. Mean values of HMI before and after the change point of magazines

Table 4. Results of change-point tests concerning newspapers

<b>Test</b>	<b>Change point</b>	<b>HMI value</b>
<i>Pettitt</i>	1978	2.1395
<i>Buishand U</i>	1980	2.1618
<i>SNHT</i>	1980	2.1618

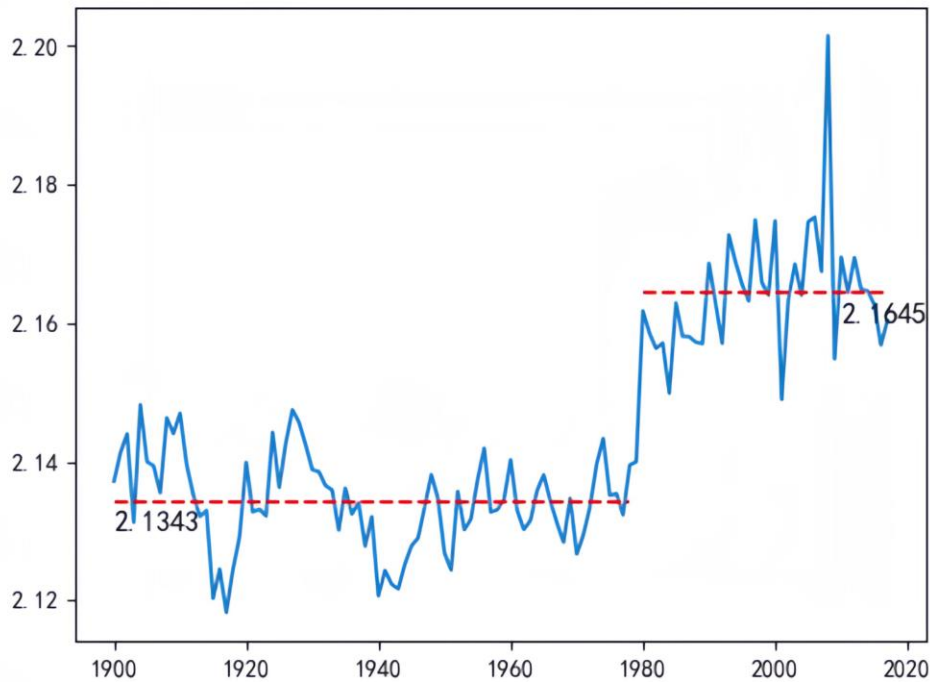


Figure 6. Mean values of HMI before and after the change point of newspapers

### 4.3. Contributions of EH-word categories

In order to examine what kinds of EH-words are preferred in American magazines and newspapers, we draw upon the EH-word categories of Westbury & Hollis (2018), which were already introduced in Section 3.3.4. To be specific, we computed the cosine similarity values between each EH-word category and the 100 EH-words that contribute the most to the HMI values of each decade.

Figure 7 displays the similarity between the 100 selected EH-words of magazine texts in each decade and each of the six EH-word categories. Among the six word categories, the similarity values to the animals category are the highest in most of the decades, except the 1900s and the 1960s. The word category with the highest similarity value in the 1900s is the sex category while that in the 1960s is the party category. In contrast, the insults category and the profanity category have the lowest similarity values in most of the decades. This finding suggests that American magazines tend to use fewer negative or offensive EH-words across these decades, as the insults category and the profanity category contain derogatory terms used to offend others or show disrespect.

Figure 8 presents the similarity between the 100 selected EH-words of newspapers in each decade and each EH-word category. It can be seen that the animals category and the party category have the strongest association with the selected EH-words in most decades. With regard to the two offensive EH-word categories, that is, the insults category and the profanity category, their associations with the selected EH-words are at a relatively low level in general, except for the period between the 1910s and the 1930s. The finding indicates that offensive and derogatory EH-words are not favoured in American newspapers.

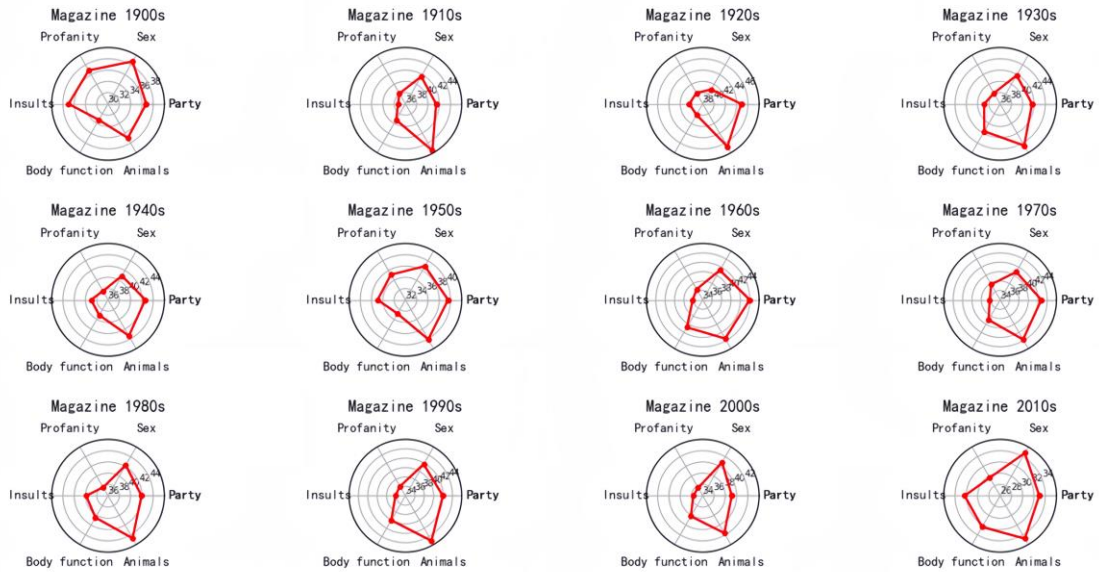


Figure 7. Similarity values of top 100 EH-words of magazines in each decade to six EH-word categories

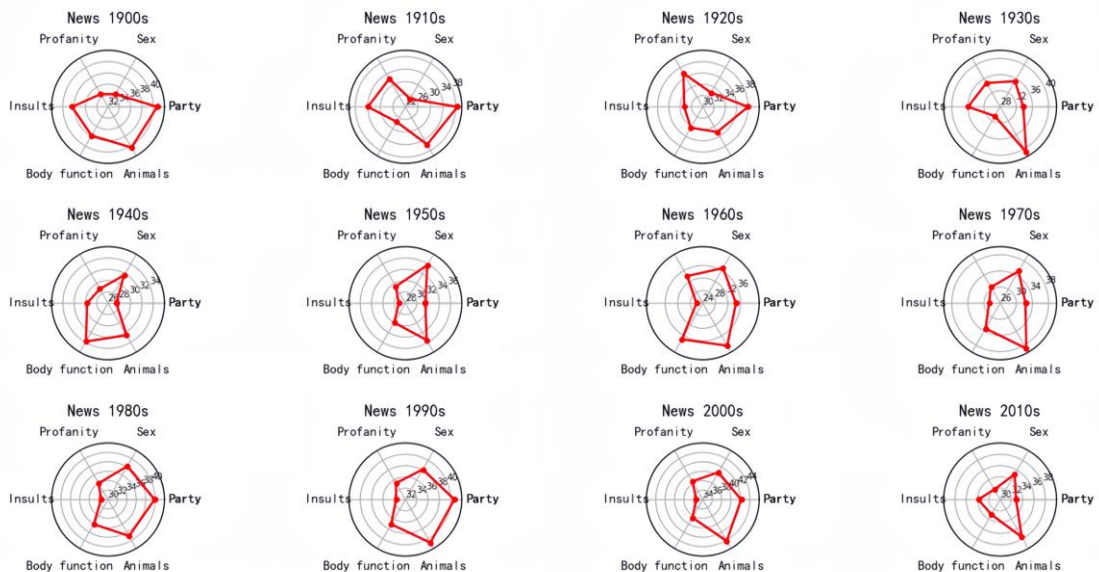


Figure 8. Similarity values of top 100 EH-words of newspapers in each decade to six EH-word categories

## 5. Discussion and conclusion

The present study explored changes of the degree of humour in American magazines and newspapers based on a large dataset across 118 years. It was found that the HMI values of magazines were significantly higher than those of newspapers. Meanwhile, magazines and newspapers have displayed similar diachronic trends in the change of HMI values. An upward trend of HMI values was observed in both genres and abrupt jumps were detected in both genres

towards the end of the 20th century. Moreover, contributions of the two offensive EH-word categories (*insults* and *profanity*) were found relatively low, which indicates that derogatory EH-words were used less frequently than other types of EH-words. Below, we discuss the efficacy of HMI and possible explanations for our findings.

In order to measure whether the HMI indeed detects humorousness, we present several examples derived from the corpus data. Sentences in italic type are rated as humorous (HMI value > 3) and EH-words are highlighted in bold type. Their co-texts are also given for readers to better assess their degree of humour.

(2)

A man who identifies himself as Dr. Jose Senaris is shown in a video discussing "Game of Thrones" leaks he posted to YouTube. *He **jokes** President Barack Obama was his **source**.*

(magazine\_2016\_ 4174626)

(3)

Men crave reassurance about their appearance just like we do, and if you're not telling him he's attractive, he may look to other women for it. Singling out an erogenous zone like his butt will make him feel objectified ... in a good way. *Plus, it's the **perfect** opportunity to initiate some playful **ass-grabbing**.*

(magazine\_2010\_ 4083028)

The HMI value of the italic sentence in (2) is 3.15 and that of the italic sentence in (3) is 3.04; the two sentences are identified as humorous according to their HMI values. Through analysing their humorousness with the combination of contexts, we attempt to examine whether their degree of humour matches their HMI. Example (2) talks about a man who leaked a famous film. The man made a joke about his information source. The source he claimed was President Obama, which appeared absurd since Obama is almost impossible to know him and also unlikely to spoil the plot even if he knew it in advance. The absurdity creates humorousness, which is consistent with the result of HMI. As for (3), it is a suggestion for how women are supposed to treat men. There is an incongruity between the italic sentence and its previous sentence. After stating the sense of objectification triggered by the sexual behaviour, the example clarifies that it is "in a good way" and then recommends it. The incongruity intensifies the playfulness and funniness of this example, also coinciding with the measurement of HMI. More examples rated as humorous and their contexts are shown in Appendix A to allow readers to evaluate the face validity of this method.

With regard to the first research question, the results of descriptive statistics and a t-test suggested that the degree of humour of magazines was overall higher than that of newspapers. This difference in humour may be explained by the different linguistic features of the two genres. It is believed that the language style of newspapers is more objective than that of magazines (Lazarsfeld, 1942). This is because newspapers cover current affairs and therefore have the responsibility to record facts, while magazine articles often aim at analysing events and expressing opinions, which would generate a personal style. In addition, newspapers may also adopt a more conservative and formal writing style (Conboy, 2010) while magazine articles may be comparatively informal and reader-friendly in language (Fowler & Smith, 1979). As a result, newspapers tend to be more rigid in style while magazine articles appear more flexible. Because of such differences, it may be easier for humorous language to make its way into magazines.

(4)

Montgomery County Executive Isiah Leggett is weighing whether to approve or veto a bill that would raise the minimum wage to \$15 per hour by 2020 -- legislation that narrowly passed the all-Democrat County Council. Montgomery County is the first metropolitan jurisdiction to approve a



minimum wage increase since the District enacted a wage hike last year. County lawmakers on Tuesday approved the bill in a 5-4 vote, meaning the council would be unlikely to override a veto if Mr. Leggett strikes down the legislation.

(newspaper\_2017\_4192381)

(5)

La La Land is a movie carried by talented actors doing their best with what they were given. One of the things they were given was this hideous souffle-cake chimera which Ryan Gosling believably portrays as food. What is it? A grotesquely constructed egg and green souffle made of 100 eggs? A moldy yellow cake? Round flat bread? A tall pizza? 1,000 crepes stacked on top of one another? What fucking food fucking looks like this?

(magazine\_2017\_4180856)

The examples were taken from COHA and both were published in the year 2017. (4) is a text of news reportage on a bill concerning the increase in the minimum wage. (5) is an excerpt of a magazine article commenting on a famous film. In terms of the degree of humour, (5) whose HMI value is 2.29 exceeds (4) whose HMI value is 2.13. This is partly because (5) leaves readers with the impression of being quite rigid and formal, and such a serious frame leaves little room for humorous language. In contrast, (5) seems more informal, colloquial, and playful in linguistic style. Such a discourse would naturally employ many words that help generate a sense of humour (e.g., *fucking*).

In terms of the second research question, the results of trend analysis and the change-point detection revealed a rising trend in HMI values in the two examined genres, and showed that the change point was 1992 for magazines and 1980 for newspapers. They showed that both magazines and newspapers were gradually inclined to adopt more humorous words especially in the last two decades of the 20th century. The increasing use of funny language may be attributable to the phenomenon of infotainment as discussed in previous studies (Boukes, 2019; Brants & Neijens, 1998; Delli Carpini & Williams, 2001). A compound coined by combining information and entertainment, the term *infotainment* refers to the trend that media texts are becoming more entertaining and amusing, and easily accepted by the public in language use and presentation modes (Boukes, 2019; Delli Carpini & Williams, 2001). Such a trend may have been driven by the increasingly fierce media competition (Patterson, 2001), the changing interests of readers (Boukes, 2019), and the influence of new media forms (Delli Carpini & Williams, 2001). Davis et al. (2020) pointed out that the use of humour is an important strategy usually employed to realise infotainment, since it helps increase the entertaining level of contents. It is reasonable to assume that the use of humour strategy would be represented at the lexical level by using humorous words. With the use of more humorous words in news reportage, the rigid style may be weakened to create a more relaxing, delightful, and interactive reading experience. Besides, it was in the 1980s that infotainment sprang up and gained influence in the media world (Delli Carpini & Williams, 2001; Patterson, 2001), which shows a temporal coincidence with the timing of change points of HMI values. This probably explain the sharp increase in the HMI values of the media texts in the 1980s and 1990s as found in this study. Apart from the potential influence of infotainment, some other parameters concerning linguistic changes may also cause the abrupt jump of HMI in the late 20th century. These parameters include conversationalisation (Fairclough, 1995), colloquialisation (Rühlemann & Hilpert, 2017), and popularisation (Biber, 2003). Conversationalisation and colloquialisation describe a similar trend to shift written style into spoken style (Fairclough, 1995; Rühlemann & Hilpert, 2017). With such a shift, public language tends to become informal and less rigid, and thus may provide more room for humour. Popularisation is an inclination of written language becoming more accessible and easier-to-comprehend to attract more audiences (Leech et al., 2009). Since

the rise in HMI is possibly a need for media to appeal to wider readers, it may be regarded as one of the consequences of popularisation.

Taking the more conservative style of newspapers into account, we also try to speculate why the timing of the change point of newspapers is one decade earlier than that of magazines. According to Biber & Gray (2013), in most cases, the newspaper they studied is more innovative in linguistic features than the magazine. In other words, newspapers are likely to take the lead in historical developments. Conboy (2010) also believes that though newspapers are conservative in style, they also want to express radical implications and welcome changes. The earlier timing of newspapers to employ funnier language may be influenced by their stronger willingness to lead the way.

As for the third research question, it was found that among the six EH-word categories, the animals category and the party category have contributed the most to the degree of humour of media texts. The party category, as mentioned before, is concerned with having good times and enjoyment, which implies a positive trend in the lexical use. An example containing EH-words with high similarity to the party category in humorous passage is as follows:

(6)

And, every now and again when Carter is on patrol and sees a dog walker, he stops and says hello. "I say, 'Hey, it's a city ordinance, I have to stop and pet your dog,'" Carter said. "*They always get a **chuckle** out of that.* People who own pets have a lot of love to give."

(newspaper\_2015\_4137606)

The EH-word *chuckle* is highly associated with the party category in the 2010s with a similarity value of 0.40. The HMI value of the sentence in italics is 3.69, indicating a relatively high degree of humour. In this example, the narrator Carter made a joke about an ordinance that did not exist at all so as to have fun with pets. The word *chuckle* suggests the enjoyment and fun perceived by the receivers of the joke, both of which belong to positive emotions.

As for the animal category, we carried out further analysis to examine how EH-words of high similarity to this category are used. We extracted all words whose similarity values to the animal category are higher than the average similarity value from the 100 examined EH-words in one decade for each genre. Later, we classified these words according to their semantics and their use in co-texts. The results of the classification showed that most words are indeed associated with animals and human beings, such as animal names (*dodo, pooch, cuckoo*), words to address people (*stooge, nitwit, geezer*), body parts of creatures (*booty, tit, crotch*), and actions of creatures (*waddle, snort, jabber*). Such types of words happen to be one of the foci of media, because media are usually required to record the object and the process of an event. Consequently, it is reasonable to infer that the great contribution of the animal category to humour results from the characteristics of the media register.

In contrast, EH-words with derogatory or offensive meanings, such as those in the insults category and the profanity category were found the least frequently used in many decades (see Figures 7 and 8). One humorous example with derogatory EH-words is shown below.

(7)

People buy anyway because they assume that house prices will keep rising, meaning they can sell out later for a profit. [...] But that can't go on forever: At a certain point the high price of land will drive away the very economic activity that made the land valuable. In other words, this real estate market craziness can not continue. But to make a bet about when it's going to end-now that would be really crazy. Yes, asset prices have gone wild. *And **nitwits** are getting really **rich**.*

(magazine\_2005\_418250)

Example (7) whose HMI value is 3.33 triggers humorousness by mocking and insulting people who buy houses irrationally. Both the word *nitwit* and the word *rich* are EH-words. Especially, the word *nitwit* is relatively highly linked with the insults category in the 2000s with a similarity value of 0.38, and takes the predominant role of the generation of such disparaging humour in the example.

The contrast in the humour contributions from the party category and the two derogatory categories may be linked with certain linguistic universals such as the linguistic positivity bias (Augustine et al., 2011; Rozin et al., 2010). Linguistic positivity bias, or the Pollyanna principle, denotes the inclination to use positive words more often than negative words in human interactions (Augustine et al., 2011; Rozin et al., 2010; Wen & Lei, 2022). Previous studies have shown that linguistic positivity bias may exist in different languages and registers (Dodds et al., 2015). Humorous language also has positive and negative distinctions. Amusing humour boosts positive emotions while some kinds of humour, such as mockery, threaten people's well-being and then trigger negative sentiments (Martin, 2007; Warren et al., 2021). Example (6) and (7) in this study confirm the existence of positive and negative humorous language. The outperformance of the party category over the two derogatory categories can be seen as a manifestation of humorous language in linguistic positivity bias. Hence, the findings of the present study have complemented these studies from a new perspective. That is, we have provided further evidence for linguistic positivity bias by showing that the tendency to use less negative language and more positive language also exists in the humorous language of media texts.

In conclusion, the present study has investigated humour in American media discourse and found out possible reasons of the change of humour. This study has both theoretical and methodological implications. Theoretically speaking, the study has provided further support for the trend of infotainment and the existence of linguistic positivity bias from a new perspective, that is, humorous language in media texts. Methodologically speaking, this study sheds light on how the degree of humour can be measured in language and texts based on a bag-of-words approach. We employed a large-scale diachronic corpus to render scientific findings with validity and generalisability. We also show the usefulness of several statistical tools in humour research.

The following limitations may be addressed in future research. First, from the perspective of methodological choice, the present study only considered humour at the lexical level, following the humour ratings and presuppositions of Engelthaler & Hills (2018). Although this bag-of-words method is of higher interpretability than other machine-learning models and detects humour in miniature, it neglects humour generated at other levels such as context, phonology, syntax, etc. In this manner, the accuracy of the bag-of-words model in predicting humour may be impacted. Thus, future studies may incorporate more sophisticated models with higher interpretability into diachronic humour studies. Second, a possible limitation of the present study is to use the humour norms in 2018 to represent humour in the past decades. This is partly attributed to the lack of investigations concerning humour norms in other periods. In addition, this study is based on the media texts collected from COHA, which belongs to American English. It would be interesting to validate the findings of this study with other English varieties or genres, which is conducive to the exploration of human language universals.

## **Appendix A: Examples of sentences rated as humorous in context**

The below table presents 20 examples, which are ordered according to the HMI value of the sentence rated as humorous. Sentence rated as humorous are marked in italics and EH-words are in bold.

Example	HMI value	Source
But what's so revealing about Feud is that it shows exactly how much they suffered against unbelievable odds. "You know who you remind me of? Not John Ford." Alfred Molina's horror at the thought of going back to television. <i>"This is about Crawford's <b>tits</b>."</i>	4.25	Magazine_2017_ 4185674
Christian Gottlieb Barth observed in the 19th century that "anyone who does not believe in the universal restoration is an ox. <i>[B]ut anyone who teaches it is an <b>ass</b>."</i>	3.92	Magazine_2010_ 4074692
"Within a couple of minutes, I knew he was a fraud," Clizbe says. <i>"You can't <b>bullshit</b> a bullshitter."</i>	3.61	Magazine_2016_4176743
Sometimes these works were simply escapist fantasies that distracted me from the difficulties of my internal life. But other times, in the strongest moments - maybe through the words of Alice Cooper or Freddie Mercury, through Cronenberg films, or even in Chewbacca's growl, I experienced something deeper - the realization that I wasn't completely alone. <i>Someone out there was as weird and strange and <b>whacked</b> out as I was.</i>	3.55	Magazine_2017_ 4183220
The second one up here is from my favorite genre of costumes: Ones you can simultaneously freeze and overheat in. And last ... sexy Elf on a Shelf. I hate the intrusion picked this picture because the back of this really goes the distance. <i>There are so many <b>layers</b> of flounce on that elf <b>ass</b>.</i>	3.45	Newspaper_2015_ 4185633
Facebook is embroiled in another embarrassing scandal. It appears that some users who post InfoWars articles to the social networking site are noticing that it's being marked as "spam." As everyone knows, content from InfoWars isn't "spam," it's "bullshit." Screenshots posted by InfoWars writer Paul Joseph Watson showing his posts being marked as spam when they should clearly be marked as bullshit (Twitter). Paul Joseph Watson, a writer for InfoWars noticed the "spam" designation yesterday evening. And Facebook has really screwed the pooch on this one. InfoWars is filled with loads of misinformation and conspiracy theories, like the idea that the massacre at Sandy Hook Elementary School in 2012 which killed 20 children and six adults was all staged by actors paid by the government. <i>Again, that's not <b>spam</b>, it's <b>bullshit</b>.</i>	3.44	Magazine_2017_4182104
My favorite books include the old Baseball Abstracts; I prefer them to the Brothers Grimm yes, even if	3.37	Newspaper_2013_ 4134836

<p>Kozma is looking a lot like the Frog Prince. So I'm not slamming stat heads. [...] a .308 onbase percentage and a .344 slugging percentage in 2,752 minor-league at-bats, and that isn't supposed to translate into Robin Yount. That said, I'm enjoying watching Kozma shred the sabermetric spread sheets and make paper airplanes out of the reports that suggest his bat carries traces of Mario Mendoza DNA. <i>OK, I'm a sucker (at least in this instance) for narrative.</i></p>		
<p>Nikole tried to funnel her feelings into words. "Happy" just was not big enough. It's a miracle, she said. She called Tony and when she got home, he was of wonder on his face. <i>They grinned at each other and could not stop.</i> Then they started laughing.</p>	3.24	Newspaper_2015_4132856
<p>As Romney spoke of his plan to repeal Obama's plan, Pham nodded in agreement. "I'm all for a voucher plan," Pham said. "You need competition. <i>I have to bust my (butt) to be competitive.</i>"</p>	3.20	Newspaper_2012_4127755
<p>I walked on that set like, "What the hell?" Clinton remembers. "I see a big fake ass in the corner--oh guy. <i>Oh, that's coming out your ass.</i> Ok, this is a new level. Just roll with it."</p>	3.18	Magazine_2017_4180656
<p>His home is a de facto museum. A shelf inches from the ceiling in one room supports his diverse team of players, politicians, cartoon characters and others. Some are recognizable, others are nameless. Some stare, others pose in action. <i>The juxtapositions are as wonderful as Manak's laughter, which he sprinkles throughout conversation.</i></p>	3.17	Newspaper_2017_4198553
<p>In just over a minute, FutureDeluxe, a creative production studio from the UK, presents the banana in all its forms. Banana phone. Banana fan. Banana fish. Banana boat. Banana lost in thought. Banana smoking a cigarette. Banana seductively unpeeling. Banana getting its "Dole" sticker. There's also an achingly uncomfortable shot of an unsheathed banana very slowly inching toward a glass of milk. <i>Some of the incarnations are funny banana puns and others are simply personifications of our own existence.</i></p>	3.15	Magazine_2016_4175303
<p>Is the money not fulfilling, Justin? Are the millions of adoring fans not fulfilling? <i>Is the ability to acquire and then dump a living, breathing monkey not fulfilling?</i></p>	3.15	Magazine_2016_4175509
<p>When Jed Hughes was an assistant coach under Hall of Fame coach Chuck Noll with the Steelers in the 1980s, the extent of rookie hazing was telling them they had complimentary turkeys waiting for them at a local grocery store. <i>When the rookies arrived and asked for their free turkeys, the joke was on them.</i></p>	3.13	Newspaper_2013_4135364
<p>Cardi B was definitely the artist who won the most new fans, from her "Bodack Yellow" performance on</p>	3.09	Magazine_2017_4180684

the red carpet to her horrified face at Ed Sheeran. Her finest moment came when she raved about Colin Kaepernick—“As long as you kneel with us, we’re gonna be standing for you! That’s right, I said it!”-- <i>while <b>holding up her dress to avoid unleashing her left boob upon the world.</b></i>		
A sailboat, it has often been said, is a hole in the water into which one pours money. <i>Weekend sailors <b>joke that boat is an acronym for Bring Out Another Thousand.</b></i> A used 18-ft. sloop can cost \$10,000, while a new 36-ft. two-masted ketch can run \$100,000 and up. And then there's the maintenance and the commitment to sail from a single port.	3.09	Magazine_2002_373482
<i>Jessica Rinaldi/Globe Staff Lestra Litchfield of Cambridge <b>joked with her daughter Lestra Atlas as they and others gather to knit “pussy hats” during a knit along at Gather Here in Inman Square.</b></i>	3.08	Newspaper_2017_4198379
You can have a charming newcomer like Barack Obama, ascending like a political Pegasus, who loses altitude because it turns out he disdains politics. <i>It’s always a <b>pig in a poke.</b> So why not a <b>pig who pokes?</b></i> It will cause winces and grimaces and Mr. Trump can go badly astray, as he did with the president’s birth certificate.	3.06	Newspaper_2015_4137301
“Everyone is always wrong, Kevin Slaten is always right,” Romanik sarcastically said and added that Slaten’s approach is, “I never made it, so I’m going to talk about people who have.” He also took a shot at Slaten for having worked at many stations and now going to 920, which has much less wattage than 1190. “If he’s such a big shot, why has he been all over the dial?” <i>Romanik asked and ridiculed Slaten’s “carpe diem” <b>catchphrase:</b> “You can carpe-diem your (butt).”</i>	3.05	Newspaper_2013_4134924
In fact, Thurber confirms, Aniston “doesn’t get enough credit for how funny she is in person. <i>She has a real <b>kind of fun, wicked wit about her.</b></i> She's able to laugh at herself. She doesn’t take herself seriously. ...You can’t embarrass her.”	3.02	Newspaper_2013_4129010

## Appendix B: The whole process of establishing HMI of a particular text

Appendix B presents all steps of establishing the HMI value of a text, with the text newspaper\_1906\_677371 in COHA as an example. The whole process to calculate its HMI is as follows.

1. Count the word frequency of all the words that appear in the text. The output is:

Word	Freq.	Word	Freq.	Word	Freq.	Word	Freq.
the	43	island	2	settle	1	hundred	1
be	24	into	2	servant	1	home	1
of	20	indispensable	2	scripture	1	his	1
in	15	gratuitous	2	rest	1	hear	1
that	10	from	2	region	1	flatly	1
and	10	fight	2	quite	1	far	1
a	9	entirely	2	protect	1	exception	1
to	7	condition	2	possible	1	everybody	1
philippines	6	chinaman	2	population	1	even	1
labor	6	by	2	polity	1	european	1
an	6	as	2	philippine	1	everybody	1
man	5	against	2	paragraph	1	entire	1
for	5	zone	1	own	1	electoral	1
experience	5	york	1	outlet	1	east	1
do	5	yet	1	our	1	early	1
can	5	year	1	ought	1	drug	1
which	4	would	1	other	1	dozen	1
tropics	4	without	1	one	1	down	1
this	4	whatever	1	on	1	domestic	1
they	4	what	1	north	1	differently	1
state	4	west	1	nonsense	1	demagoguery	1
it	4	way	1	no	1	declaration	1
if	4	want	1	new	1	course	1
chinese	4	van	1	need	1	country	1
american	4	useful	1	necessarily	1	could	1
all	4	up	1	naughtiness	1	contradict	1
able	4	trader	1	native	1	continental	1
wedge	3	time	1	my	1	contest	1
properly	3	thousand	1	most	1	colony	1
not	3	then	1	moreover	1	chinamen	1
manual	3	than	1	moment	1	chief	1
hearst	3	temperate	1	might	1	care	1
he	3	talk	1	mere	1	capacity	1
have	3	tabor	1	martin	1	candidate	1
enter	3	syracuse	1	market	1	campaign	1
at	3	surplus	1	mankind	1	call	1
work	2	superfluous	1	make	1	but	1
who	2	superfluity	1	long	1	bring	1
white	2	supererogatory	1	life	1	believe	1
we	2	suggestion	1	lie	1	become	1
united	2	such	1	lesson	1	avoid	1
treat	2	speech	1	leave	1	assumption	1
think	2	speaker	1	learn	1	alone	1
there	2	south	1	lated	1	almost	1
supply	2	soldier	1	late	1	alike	1
sheer	2	soil	1	its	1	agree	1
oriental	2	single	1	issue	1	admission	1

or	2	silly	1	inculcate	1	administration	1
mean	2	silliness	1	imagine	1		
let	2	should	1	i	1		

2. Match words in the text with EH-words. All EH-words in the text are retrieved, and their frequency as well as humour rating are extracted. The output is:

EH-word	Humour rating	Freq.	EH-word	Humour rating	Freq.
silly	3.41	1	white	2.08	2
treat	2.74	2	lesson	2.07	1
nonsense	2.62	1	hundred	2.07	1
rest	2.46	1	one	2.06	1
mere	2.44	1	van	2.06	1
life	2.42	1	let	2.05	2
tropics	2.41	4	market	2.04	1
region	2.40	1	campaign	2.03	1
soil	2.37	1	outlet	2.03	1
north	2.26	1	call	2.00	1
supply	2.26	2	home	2.00	1
island	2.24	2	single	1.97	1
issue	2.24	1	want	1.97	1
chief	2.21	1	trader	1.97	1
scripture	2.18	1	speech	1.94	1
surplus	2.17	1	soldier	1.94	1
south	2.17	1	state	1.94	4
west	2.16	1	work	1.91	2
think	2.14	2	need	1.90	1
contest	2.13	1	year	1.87	1
moment	2.13	1	leave	1.87	1
east	2.11	1	make	1.86	1
manual	2.10	3	mean	1.84	2
man	2.10	5	settle	1.84	1
do	2.09	5	dozen	1.83	1
fight	2.09	2	lie	1.76	1
care	2.09	1			

3. Calculate the HMI value of the text according to Formula 2. The contribution of each EH-word in the text are first calculated by multiplying their humour rating and frequency (*Humour rating \* Freq.*). The overall contribution of all EH-words in the text is the sum of the contribution of each EH-word. Through dividing the overall contribution (166.36) by the total frequency of all EH-words (78), we gained the HMI value of the text (2.13).

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