Laughter Computing in TED Talks

(TED Talks における笑いの計算)

July　２０２２

Vera Paola Reyes Shoda

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School of Integrative and Global Majors

Ph.D. Program in Empowerment Informatics

University of Tsukuba

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Chapter 1

Introduction

How would you incorporate audience laughter in presentations and speeches? How about building robots and virtual agents that can detect or predict audience laughter? While there has been extensive research on laughter detection in digital media, very little research exists in measuring the quantitative and linguistic characteristics of audience laughter in presentations. Specifically, studies on measuring the frequency and placement of audience laughter are lacking. Therefore, this study aims to contribute to research in laughter computing and prediction, focusing on TED Talks by discovering features that can be used to represent humor.

Notably, this study explored how to measure audience laughter frequency and placement using natural language processing (NLP). Laughter computing was studied using transcripts of presentations from TED Talks (www.ted.com/talks). The findings of this research are expected to empower applications in laughter generation, detection, and prediction and contribute to human informatics research.

1.1 Problem Statement

We do not know how often or where to place audience laughter in presentations or speeches for the best effects on audience engagement and experience. Related studies on assessing laughter frequency in traditional classroom settings found that the context in which teachers evoke student laughter varies with their experience, popularity, and credibility. In educational lectures, previous literature showed that, on average, students laughed once every 15 minutes during a 50-minute lesson. However, these studies were dated four decades ago, and we have no idea about the current audience laughter context in presentations.

1.2 Purpose of the Research

This research aims to study audience laughter in presentations using TED Talks and the application of computational techniques. How often is audience laughter in presentations? Previous studies showed that student laughter in traditional learning environments, on average, was once every 15-20 minutes. However, we do not know if the same is true for presentations. Similarly, it is not known where laughter should be placed during the presentation timeline. Where should audience laughter be set in the presentation timeline? Timing is essential, and the effects of laughter on the audience experience can change depending on its usage and incorporation. In addition, we do not know if the laughter incorporation of presenters in TED Talks and teachers in traditional classroom settings are the same or not. Does the format and environment of TED Talks change the way presenters use audience laughter compared to teachers in traditional classroom settings? Lastly, machine learning applications are finding ways to create robots or virtual agents with personalities – one of them being capable of evoking laughter. However, it is unclear if humor used in the TED Talks context is the same as humor used in non-TED content. In addition, there is still a lack of quantitative features such as laughter interval and placement that are used in learning algorithms for predicting audience laughter. Therefore, based on these questions, this research was conducted to measure audience laughter in TED Talks.

The corpus used in this study is transcripts of presentations from TED Talks and user-submitted jokes scraped from the internet. TED Talks are a collection of presentations done at TED sponsored conferences and events. This study used natural language processing (NLP) techniques to measure audience laughter in TED Talks.

The value of this study is that it provides new information on audience laughter in TED Talks. The study also aims to discover features used in machine learning applications to predict audience laughter in presentations or speeches. Likewise, the methodology used in this study is replicable, and findings are expected to apply to empowering people in laughter adoption to improve the audience experience. Academically, the contribution of this study is to advance our knowledge in laughter computing and human informatics.

1.3 Research Questions and Thesis Outline

The goal of this study is addressed by exploring four main research questions (RQ) and hypotheses (H) as follows:

- **RQ 1.** How often is audience laughter in TED Talks? Is there a difference between audience laughter occurrences between popular and less popular presentations?
- **H 1-1.** Audience laughter is used very frequently.
- **H 1-2**. The frequency of audience laughter affects the popularity of the TED Talks.

- **RQ 2.** How is audience laughter placed in the presentation timeline?
- **H 2-1.** Humor is placed at the start of the presentations since this placement is best considering the cognitive load burden for the audience.
- **H 2-2.** Humor is placed in the middle of the presentations to serve as a break.
- **H 2-3.** Humor is placed at the end of the presentations to increase the positive experience of the audience.

- **RQ 3.** How different or similar is audience laughter in TED Talks from student laughter in traditional classroom settings?
- **H 3-1.** Audience laughter in TED Talks is more frequent.
- **H 3-2**. Educators and presenters who are more popular, experienced, and credible evoke audience laughter more frequently.

- **RQ 4.** How different or similar are the linguistic features of humorous sentences used in TED Talks with non-TED content?
- **H 4-1.** There is no difference in the linguistic features.

To investigate these research questions, an interdisciplinary approach was used. RQ 1 is to explore the audience's laughter frequency in TED Talks. This question was examined using computing perspectives, natural language processing, and statistical tests (see Chapter 4). RQ 2 is to explore the placement of audience laughter in the presentation timeline. This question was investigated from psychological and computing perspectives using surveys, natural language processing, and visual analysis (see Chapter 4). RQ 3 compares the audience laughter in TED Talks and student laughter in traditional learning environments. This question was investigated from a computing perspective using natural language processing (see Chapter 4). Finally, RQ 4 is to compare the linguistic characteristics of humor for TED talks and non-TED digital media content. This question was investigated from linguistic and computing perspectives using computational linguistic approaches (see Chapter 5).

This dissertation includes seven chapters. Chapter 1 addresses the outline of this research. Chapter 2 introduces the research background. Based on the literature review, the methodology was adopted to measure audience laughter. Chapter 3 is dedicated to clarifying the relationship between humor and laughter. Chapters 4 to 5 are to explore RQ 1 to RQ 4 using interdisciplinary perspectives. The research discussion, limitations, and future work are addressed in Chapter 6, and finally, the conclusion of this research is discussed in Chapter 7.

Chapter 2

Background

2.1 Definitions and Theories of Humor and Laughter

Researchers in a variety of ways define humor. Superiority, incongruity, and arousal relief are the most popular theories in humor research (Scheel, 2017). Superiority theory, which has been prevalent since the time of Plato and Aristotle, explains that laughter is an effect of a feeling of superiority due to the depreciation of other people (Gruner, 1978). Incongruity theory argues that something is perceived as humorous when there is a contradiction or unexpected outcome (Berlyne, 1960). In the arousal theory, Berlyne said that "humorous situations always contain factors that can be expected to raise arousal and other factors that can be expected to lower arousal or else keep it within moderate bounds (Berlyne, 1969) (p.861)." Another interesting theory in humor research is the anxiety theory, which states that laughter results from tension release (Koestler, 1949).

Laughter is considered a universal language recognized by humans (Sauter et al., 2010; Savage et al., 2017). There are various situations where laughter is manifested, such as feelings of shock, playfulness, surprise, or indifference (Willman, 1940). Using laughter in the classroom is a commonly used technique by teachers. Teachers are aware of the benefits of laughter to their students' performance (Omede & Daku, 2013), and previous research has shown its positive effects (Robinson, 1983; Cueva et al., 2006; Banas et al., 2011). For example, Humor-Integrated Language Learning (HILL) which is a growing field in TESOL (Teaching English to Speakers of Other Languages) (Bell & Pomerantz, 2016), has shown that integration of HILL in TESOL can bring constructive effects on both students and teachers (Heidari-Shahreza & Heydari, 2018) These studies on HILL in English language education focus on the humor styles, awareness, students, and teachers' perspectives (Heidari-Shahreza & Heydari, 2018), and techniques teachers employ in the classroom (Schinickel & Martchev, 2017). Similarly, other studies on the usage of laughter in higher education identified the types of laughter that professors use (Nesi, 2012).

Since humor has several functions aside from being a tool used in education (Banas et al., 2011), in this paper, we will refer to humor used in an educational context as instructional humor. Prominent theories in instructional humor include the Instructional Humor Processing Theory (IHPT), which explains that the students need to perceive and solve the paradox in humor to ease their learning (Wanzer et al., 2010). Another related research links the Cognitive Load Theory (Sweller, 2010) to humor application in STEM education. Humor in STEM education should be integrated into the intrinsic cognitive load to be effective (Hu et al., 2017). The studies in instructional humor can be divided further into quantitative, qualitative, individual differences, effects, and theories (Banas et al., 2011).

Similarly, the art of making students laugh in digital education has various applications. For example, in e-learning, several chatbot learning programs focus on making virtual agents that can bring about laughter to stimulate learning and keep students' focus and interest in the lesson (Dybala et al., 2010). Other applications of using laughter in pedagogy are effective content creation of learning materials and teaching methods. Correspondingly, previous research uses television comedy programs to teach political science to increase student engagement and outcomes (Beavers, 2011).

2.2 TED Talks

This study used Ted Talks as the source corpus. TED Talks cover various topics from humanities, social sciences, natural sciences, design, global issues, technology, and business. Speakers also come from different backgrounds such as academe, industries, media, and entertainment. Having this interdisciplinary and diverse culture, TED Talks can reach a wider audience than the usual academic conferences. TED Talks are engaging, fun, creative, and appealing. TED Talks use various methods to capture and keep their audience's interest, such as laughter, story-telling, and other forms of entertainment.

Previous researchers have analyzed TED Talks before regarding the background and characteristics of speakers and the effect of the talk on the popularity and citation of speakers. Furthermore, another focus of studies is on the demographics of audiences (Sugimoto et al., 2013), creating linked data for education (Taibi et al., 2015), and the development of navigation graphs for users to help students browse videos (Hu & Li, 2017). Despite the extensive research on TED Talks, there is still a lack of analysis on the presentations' content, mainly the frequency of audience laughter and its placement in the presentation timeline.

2.3 Machine learning

Machine learning involves creating algorithms that enable computers to improve performance through learning from experience (Jordan & Mitchell, 2015). It has been applied to various fields, such as entertainment, education, and medicine (El Naga & Murphy, 2015). Typical machine learning applications involve computer vision, natural language processing and understanding, and pattern recognition models. There are four types of machine learning: Supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. This research uses supervised learning and is further explained in the next section.

2.3.1 Supervised learning

In supervised learning, we use labeled data for training models. The target of supervised learning models is to minimize the error between the target and computed output. The target output is an output that is initially labeled, while the calculated output is the result computed by the learning algorithm (Jo, 2021). This research uses two labels for the data: laughter positive in the case of audience laughter instance and laughter negative in the case of non-audience laughter.

2.3.2 Features

To improve the learning algorithm, features are used. Features are input variables or data attributes (Guyon et al., 2008). In creating models, it is essential to choose the correct features that accurately describe the data and the combination of those features to increase the learning performance of computers. Previous works in laughter computing used features such as sentiment, word frequencies, and linguistic properties of jokes (Acosta, 2016). Selecting features to represent the data is essential and has received significant attention in the literature (Blum & Langeley, 1997).

2.3.3 Natural language processing

The literature describes natural language processing (NLP) as using computational techniques to analyze texts at single or multiple levels of linguistic analysis, aiming to output human-like language processing in various tasks (Liddy, 1999). NLP is built on mathematical and linguistic foundations. NLP heavily draws from elementary probability theory and essential information theory in mathematics and parts of speech, morphology, semantics, and pragmatics in the linguistics field (Manning & Schutze, 1999). NLP techniques are applied in humanities, natural sciences, and social sciences research. NLP can help researchers in text data analysis by performing tasks such as assessing subjectivity, linguistic features, and classification. Examples of NLP techniques include sentiment analysis, which can classify text as negative, neutral, or positive (Medhat et al., 2014). Other methods include named-entity recognition (NER), wherein important nouns and pronouns are identified in a text (Mohit, 2014), and sentence segmentation, which splits a large chunk of text into sentences (Palmer, 2000).

Chapter 3

Humor and Laughter

Humor and laughter play an essential role in communication and are commonly used to elicit various emotions. Humor and laughter are widely studied in multiple fields such as psychology, linguistics, neurosciences, and psychiatry. However, despite much research in the area, very few have examined the relationships between the studies conducted in the field and how this research defines or relates the concepts of humor and laughter. Previous studies have shown literature reviews in their research. Still, none has focused on bibliometric analysis and presented an in-depth analysis of the relationship between the concepts of humor and laughter. A bibliographic review or analysis is essential because it focuses on the topic and identifies the authors, valuable research, approaches, and high-impact journals (Cavazza et al., 2019). Therefore, this paper reviews past literature on the relationship between humor and laughter and conducts a bibliometric analysis using a bibliometric tool, VOSViewer (Van Eck and Waltman, 2013). Studying the relationships of research on humor and laughter is vital to give us insights into how this field is approached and obtain possible directions for future research. It is also crucial for beginners in the area to have an overview of the background of the research field.

3.1 Methods

In this chapter, to reveal the relationship between humor and laughter, first, the study conducted a literature review and then proceeded with bibliometric analysis. The complete workflow for the methodology in this research is shown in Figure 1. The bibliometric tool VOSViewer (Van Eck and Waltman, 2013) and descriptive statistics were utilized to create visualizations and analyses. This section describes the dataset and the types of research that we conducted.

The Web of Science database was used to collect data on humor and laughter research. The Web of Science database contains a collection of high-quality research articles, and it is commonly used to find previous and related works in various research fields (Chen et al., 2014). Research that contained the keywords' humor' and 'laughter' was examined. This search resulted in 1326 articles from 1900 to 2021. Next, these search results were downloaded into a plain text file (.txt) used as the dataset during the analysis using VOSViewer.

The bibliometric tool VOSViewer was used to create the bibliometric maps in this research. VOSViewer is free software that allows researchers to create visualizations such as keyword co-occurrences, co-citations, and co-authorship from bibliometric data of research articles (Van Eck and Waltman, 2013). Analysis conducted includes studying the development of the number of publications and citations per year, top subject categories, and most mentioned research documents.

3.2 Results

The most notable theories on humor are the superiority theory, arousal theory, and incongruity theory (Scheel, 2017). Laughter as an effect of a feeling of superiority with the depreciation of other people is explained in the superiority theory (Gruner, 1978). In comparison, the arousal theory states that "humorous situations always contain factors that can be expected to raise arousal and other factors that can be expected to lower arousal or else keep it within moderate bounds (p.861)" (Berlyne, 1969). Lastly, the incongruity theory argues that something is perceived as humorous when there is a contradiction or unexpected outcome (Berlyne, 1960). Another prominent theory of humor is the relief theory, wherein humor occurs because of a feeling of relief from which an expected outcome did not happen (Shurcliff, 1968).

Laughter is considered a social stimulus rather than an expression of emotion (Provine, 1996), and it is said to be more ancient than humor or speech (Provine, 2001). However, other research defines laughter as a component of a universal language of basic emotions that all people have in common and recognize (Sauter et al., 2010; Savage et al., 2017). Other theories on laughter state that "laughter occurs when a total situation causes surprise, shock, or alarm, and at the same time induces an antagonistic attitude of playfulness or indifference" (p.70) (Willman, 1940). The evolutionary origin of laughter as a signal was a preadaptation that was gradually elaborated and co-opted through biological and cultural evolution (Gervais and Wilson, 2005). There are two types of laughter – Duchenne and non-Duchenne. Duchenne laughter is defined as a genuine laugh, while non-Duchenne laughter is non-genuine.

Although humor and laughter are closely examined and studied together in previous works, there are two views on the relationship. The first view is that laughter and humor are not co-extensive. In this view, it is vital to note that these terms are not interchangeable. Laughter is seen as a phonetic activity, while humor is treated as a cognitive concept (Trouvain and Campbell, 2019). We should treat laughter as an implied result of humor and vice versa. There are occurrences of laughter wherein there was no utilization of humor (Günther, 2003). For instance, tickling or exposure to laughing gas elicits laughter, but humor is not used in this case (Wyer and Collins, 1992). Likewise, there are also instances where humor is applied, but no laughter is observed. For example, some people may recognize the humor in communication but may not express it through laughter (Gervais and Wilson, 2005). Other research supporting this view found that most conversational laughter was not a result of jokes or stories that are structured attempts at humor (Provine, 1996; 2001). In this non-coextensive relationship between humor and laughter, one can exist with or without the presence of the other (Attardo, 2010).

The other view is that humor and laughter are co-extensive, meaning that laughter is a physical manifestation of humor, the opposite of the first view. Humor is defined as a psychological state characterized by the tendency to laugh wherein it requires that contradictory ideas are held simultaneously (Martin, 2007; Veatch, 1998). Another supporting research has proved that laughter occurs in all the theories of humor, whether it is the superiority theory, incongruity theory, or the relief theory (Wilkins, 2009). Likewise, in natural language processing, the presence of laughter is commonly used as a marker for recognizing humor (Chen and Lee, 2017). Similarly, humor and laughter are treated as a two-part adjacency pair in a media discourse analysis wherein humor is the first part, followed by laughter (Norrick, 1993; Richardson et al., 2014). Furthermore, in a study on social discourse, humor is said to invite laughter which serves as a mark for acceptance of the humorist by the group members (Coser, 1960). Table 1 summarizes the literature on the opposing views on the relationship between humor and laughter.

Table 1. Humor and laughter relationship

Relationship type	Description	Representative work
Not co-extensive	Laughter is not a physical manifestation of humor. Non-humorous stimuli may cause laughter.	Attardo, 2010; Gervais and Wilson, 2005; Günther, 2003; Provine, 1996; 2001; Trouvain and Campbell, 2019; Wyer and Collins, 1992
Co-extensive	Laughter is a physical manifestation of humor. Laughter occurs because of humor stimuli.	Chen and Lee, 2017; Coser, 1960; Martin, 2007; Norrick, 1993; Richardson et al., 2014; Veatch, 1998; Wilkins, 2009;

Although there are two opposing views on how humor and laughter are related and should be approached, there is no question that previous works have frequently discussed the two concepts in close relation with each other. A bibliographic analysis in the research field was conducted better to understand the context of humor and laughter research. Section 1 of this paper describes the introduction and background on humor and laughter's theories, definitions, and relationships. Section 2 introduces the data collection procedure and methods used in the analysis. The results and discussion are shown in Section 3, and the conclusion is presented in Section 4.

- *Development of the number of publications and citations per year*

Research analyses show that the earliest research observed in the dataset was from 1941, and the most recent was in 2021 (see Figure 2). Research in humor and laughter has increased since the 2000s, with the year 2018 having the most significant number of papers published at 110. The number of citations in the field also increases alongside publications. Although the number of publications and sources decreased in 2021, which may be caused by the timing of the writing of this paper, it can be said that interest in humor and laughter is recently increasing.

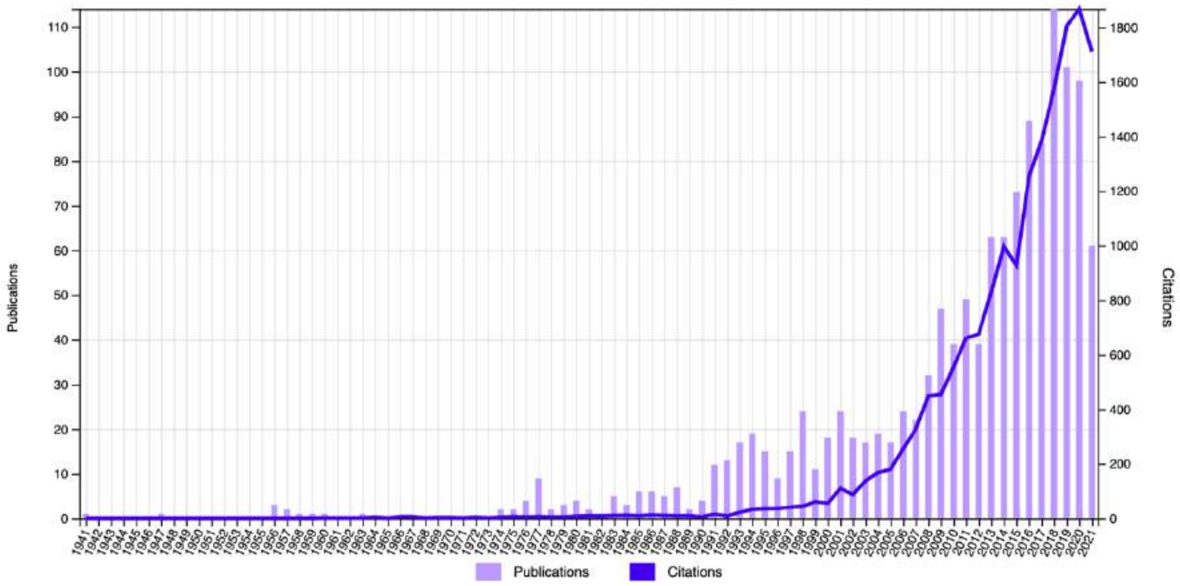

Figure 2. The number of publications and citations in humor and laughter research from 1941 to 2021.

- *Types of documents analyzed*

Research documents that were common in the humor and laughter research field were articles (73.30%), book reviews (12.67%), and proceedings papers (5.50%). Details on the counts and percentages of other documents are shown in Table 2. From this, we observe that majority of the research in the field is focused on full-length research articles rather than short communicative reports.

Table 2. Type of documents analyzed.

Document type	Record count	% of 1326
Articles	972	73.30%
Book reviews	168	12.67%
Proceedings papers	73	5.50%
Book chapters	52	3.92%
Review articles	46	3.47%
Editorial materials	45	3.40%
Early access	22	1.66%
Others	33	2.49%

The types of documents analyzed in the dataset consisted of articles, book reviews, proceedings papers, book chapters, review articles, editorial materials, early access, etc. The documents in the other category meet abstracts, books, letters, corrections, notes, and discussions (in descending order).

- *Top categories and most cited research documents*

Each of the research documents in the dataset belongs to at least one category of subjects determined by the WoS collection, which is described in the 'WoS Category' field. This field contains the subject category that each publication belongs to. Table 3 summarizes the most common WoS categories wherein research documents in the area typically fall. The research in humor and laughter is approached in multidisciplinary studies. The most popular category is *Psychology multidisciplinary,* with 272 publications or 20.51% of the analyzed documents. It is closely followed by *Language linguistics* with 267 or 20.14% of total publications. Other popular categories include *Linguistics* (5.88%), *Communication* (5.58%), and *Humanities multidisciplinary* (5.43%). Looking at the top ten categories, most research in humor and laughter tends to focus on the humanities and social sciences rather than the engineering and sciences research fields.

Table 3. Top 10 WoS subject categories in humor and laughter research.

WoS subject category	Record count	% of total
Psychology multidisciplinary	272	20.51%
Language linguistics	267	20.14%
Linguistics	78	5.88%
Communication	74	5.58%
Humanities multidisciplinary	72	5.43%
Psychology social	55	4.15%
Literature	48	3.62%
History	45	3.39%
Philosophy	44	3.32%
Sociology	44	3.32%

On the other hand, Table 4 summarizes the top ten most-cited research documents in the humor and laughter research. The most cited authors in this research field are *Martin* and *Keltner*. Most of the top-cited publications are classified under the *psychology* category. However, it is also interesting that highly cited articles are categorized under *neuroscience*, *psychiatry*, *life science,* and *behavioral science*.

Table 4. Top 10 most cited research documents in humor and laughter research.

Title	Authors	Citations	Source	Year	Category
Individual differences in uses of humor and their relation to psychological well-being: Development of the humor styles questionnaire	Martin RA et. al	775	Journal of research in personality	2003	Psychology
Humor, laughter, and physical health: Methodological issues and research findings	Martin, RA	289	Psychological bulletin	2001	Psychology
A study of laughter and dissociation: distinct correlates of laughter and smiling during bereavement	Keltner, D. et al	286	Journal of personality and social psychology	1997	Psychology
"Laughing" rats and the evolutionary antecedents of human joy?	Panksepp, J. et al	264	11th Annual meeting of the international behavioral-neuroscience society	2003	Psychology; behavioral sciences
The evolution and functions of laughter and humor: A synthetic approach	Gervais, M. and Wilson DS	263	Quarterly review of biology	2005	Life science and biomedicine – other topics
Humor modulates the mesolimbic reward	Mobbs, D. et al.	257	Neuron	2003	Neurosciences &

centers					neurology
Laughter among colleagues – a study of the social functions of humor among the staff of a mental-hospital	Coser, RL	223	Psychiatry	1960	Psychiatry
Teasing in hierarchical and intimate relations	Keltner, D. et. al	206	Journal of personality and social psychology	1998	Psychology
Benign violations: Making immoral behavior funny	McGraw, AP, and Warren, C	199	Psychological science	2010	Psychology
Conservative shift among high-exposure survivors of the September 11th terrorist attacks	Bonanno, GA and Jost, JT	194	Basic and applied social psychology	2006	Psychology

3.3 Discussions

This chapter presented a systematic overview of the relationship and research on humor and laughter through a bibliometric analysis. The literature review shows that research on humor and laughter has differing views on the relationship between the two. The first view states that laughter and humor are not co-extensive and should be discriminated while the other theory suggests that laughter is co-extensive with humor. Perhaps the difference in views may result from individual differences or personalities on how humor is perceived or recognized. Since a statement can be humorous for one person, it may not appear so for another person. Therefore, laughter may or may not follow in these situations. Future possible directions for research can be a thorough investigation of the rate wherein laughter does not or does occur given humor or vice versa to validate the research findings further. In addition, the bibliometric analysis findings showed that there are high interlinkages and connections concerning co-citations of sources and authors as well as with term co-occurrence. Thus, research in humor and laughter is closely related and grounded on past research. Specifically, keyword co-occurrence analysis showed that research in psychology shares a close link with research in the natural sciences such as neuroscience and psychiatry.

Further research can focus on bridging more research in communication and linguistics to psychology and the natural sciences. In addition, the field is highly multidisciplinary, with psychology and linguistics being the most common categories for research. Possible further research could develop the terms used in the research field through the years and provide more in-depth analysis aside from bibliometric analysis. These results offer beginners in humor and research helpful insights into the area.

Chapter 4

Laughter Frequency and Placement

Recent research focuses on the theories, effects, individual differences, and qualitative aspects of laughter and humor. However, there is a lack of studies focusing on quantitative features. Therefore, this chapter explored the quantitative characteristics of audience laughter in a naturalistic setting and applied techniques from natural language processing (NLP). This chapter describes the results of two studies. The first study focused on laughter frequency, and the second study discussed audience laughter placement and patterns. The corpus used in this research is transcripts of TED Talks.

Few literatures on laughter has focused on quantitative characteristics such as frequency and placement. Research on laughter frequency and placement are often observed in the educational context. Although several studies have looked at the quantification of using laughter in lessons, these studies are about four decades old (Banas et al., 2011). Moreover, past studies only showed the frequency of using humor in the classroom and did not analyze the placement of laughter in the lesson timeline (Gorham & Christophel, 1990; Bryant et al., 1979; Javidi & Long, 1989; Downs & Javidi, 1988). For example, professors used humor every 15 minutes (Bryant et al., 1979) in a 50-minute class session, but the placement of these jokes or student laughter was not specified.

Similarly, more recent studies use self-reported measures and frequency surveys to count laughter instances (Schickel & Martchev, 2017; Hurren, 2006; Chaniotakis & Papazoglou, 2019; Fki, 2021). In these works, research participants are asked to rate humor occurrences using adverbs of frequency terms such as *frequently*, *sometimes*, *rarely*, and *never*. Although it provides helpful insight into humor density, this method does not account for the placement of laughter in the lesson timeline and does not accurately provide quantified frequency rates.

Other related research on the placement of laughter occurs in discourse and social media message analysis. A study on the social networking site Twitter found that messages containing Typed Laughter-Derived Expressions (TLDEs) are commonly placed at the boundaries of conversational turns or edges of tweets (McKay, 2020). However, the opposite was observed in a study of WhatsApp chats, wherein laughter is seen in the posting-initial position (König, 2019). While research on laughter position exists, very little research has focused on TED Talks presentations. Therefore, the findings of this study are crucial and contribute significantly to laughter research.

4.1 Methods

The study used TED Talks as the corpus to examine the audience's laughter frequency. The study limited the talks to those conducted in the English language. Two experiments were conducted to explore the audience's laughter frequency. The laughter frequency between 50 popular TED talks and 50 least popular TED talks was compared in the first experiment. The second experiment examined the audience laughter frequency and placement patterns for the 50 most popular TED talks.

4.1.1 Experiment 1: Laughter frequency – popular and least popular talks

TED Talks website was scraped (accessed on August 1, 2021) for the first experiment to get the fifty most popular talks and the fifty least popular talks. To ensure that the least popular talks were not affected by the upload count date, only talks that had been published at least one year earlier on the TED website were considered. Likewise, only talks with 15 to 20 min duration were included in the dataset to make comparisons possible. The corpus was then divided into the most popular and least popular talk datasets since previous works in the educational context found significant differences based on the educator's teaching experience and popularity among their students and peers. Afterward, the transcript of the talks was extracted and saved in a command-separated values (CSV) file. The Pandas library in Python was used to conduct the analysis.

4.1.2 Experiment 2: Laughter placement – popular talks

In the second experiment, video transcripts in English of the TED Talks with more than 10 million views were collected to identify the audience's laughter frequencies. The study chose popular videos as a source for best practices since previous literature found that more experienced and highly rated speakers tend to use more humor and, as a result, paved the way for much better student performance (Bryant et al., 1980). The study collected fifty (50) videos with over 10 million views. However, only thirty-eight (38) videos were examined. The other twelve videos were eliminated because of transcription issues, non-usage of laughter (zero observation), presence of more than one speaker, and to keep presentation length comparable, removed talks with less than 1,000 words. The TED Talk website https://www.ted.com/talks (accessed on August 1, 2021) was scraped to extract the transcripts of the 38 most popular talks. The transcript of the talks was stored in a Command Separated Values (CSV) file. The Pandas library (McKinney, 2011) in Python was used to process the data and conduct the analysis.

While previous works had different methods to measure humor rates and locate the humorous messages, this study decided to locate the audience laughter instances using the special markup "Laughter" found in the TED Talks transcripts. This markup occurs whenever the audience laughs during the presentations. Then, these laughter occurrences were examined using statistical tests. Furthermore, the placement of laughter in the presentation timeline was analyzed. Capturing audience laughter in TED Talks transcripts was also the same for past research in automatic humor recognition (Chen & Lee, 2017).

The study looked for laughter instances by searching for the keyword '(Laugh)' in the transcripts. The position of the laughter instance was set by the word count of the keyword '(Laugh)' in the whole transcript. For example, the keyword '(Laugh)' is the nth word in the transcript. The TED Talks presentations used in this analysis consist of 2,000 to 3,000 words. It is assumed that the word count of the keyword is a better variable than time since TED Talks vary more on the duration of the speech and are affected by various factors such as speaker speaking pace, pauses, and audience reaction time. Although the methodology uses audience laughter and not individual laughter instances, previous research has found that communal laughter positively affects learning in the same way as individual laughter (Vlieghe et al., 2010).

In TED Talks, it is presumed that the speakers must deliver their presentations so that the audience can effectively understand the complex concepts and jargon. This paper supposes that generating audience laughter depends somewhat on how the speaker perceives the difficulty level of understandability. For instance, the study assumes that when speakers believe their talk has become too complex, they will use laughter to ease their audience's cognitive load. This concept aligns with using laughter as ice breakers during lessons to give students a break between the learning process (Knickle & McNaughton, 2021). Similar research also states that the text's readability score is essential since humor needs to be understandable and not distract from the instructional message (Wanzer et al., 2010). Likewise, the cognitive load theory (CLT) that focuses on humor integrated into Science, Technology, Engineering, and Mathematics (STEM) education states that if humor is not integrated into the lesson content, it will increase the students' cognitive load and lower learning (Hu et al., 2017). Thus, this paper used the Gunning Fog Index to measure the readability of the presentation transcripts. The Gunning Fog Index (see Table 5) is a standard tool for measuring the readability of texts and was developed by Robert Gunning in 1944 (Gunning, 1969). The values reflect levels of understandability of the text and the age or grade level of the audience appropriate to it. Education, marketing, and academic publications usually apply the Gunning Fog Index. A Gunning Fog Index of eight (8) and below represents an appropriate text that most people can understand or read. For academic and professional papers, a Gunning Fog of less than 15 is recommended (Gunning, 1968).

Table 5. Gunning Fog Index.

Score	Readability / educational level
6	6th grade (elementary level)
7	7th grade
8	8th grade
9	9th grade (high school freshman)
10	10th grade (high school sophomore)
11	11th grade (high school junior)
12	12th grade (high school senior)
13	13th grade (university freshman)

14	14th grade (university sophomore)
15	15th grade (university junior)
16	16th grade (university senior)
17	University graduate and above

Table 5 contains information on the scores on the Gunning Fog Index and the type of education level that can read the text. The lower the score, the easier the readability of the text. The variables in the Gunning Fog Index are the number of words in the text, the average sentence length derived by dividing the total number of words by the total number of sentences, and the number of complex words. In the Gunning Fog Index, "complex words" are those words that have more than two syllables with some exemption, such as proper nouns, compound words, and everyday words. The analysis excluded usual suffixes such as -ed, -ing, -es, and the like from counting the syllables of words (Spinks & Wells, 1993). The study used Python's textstat library (Diniz, 2005) to calculate the Gunning Fog Index.

Data on the word count position of the keyword '(Laugh)' and the text's readability level before the keyword "laugh" were collected and tabulated. After tabulation, this study plotted the data where the x-axis represents the word count (representative of time) and the y-axis, or the dependent variable is the readability level of the text before the instance of the keyword '(Laugh)' (see Figure 1). For example, '(Laugh)' was found at a word count of 100, or the keyword was the 100th word in the video transcript of one presentation. The study then calculated the readability level using the Gunning Fog Index formula on the 99 words before the keyword. The analysis used the resulting Gunning Fog Index as the value for the Y-axis. In the example shown in Figure 1, the readability score of the 99 words before '(Laugh)' has a value of 10. Therefore, in the plot, the point in the sample will have the coordinates (100, 10) where x = 100 and y = 10. The study then generated scatterplot charts for each talk, recognizing and classifying patterns. The results are described in Section 3.

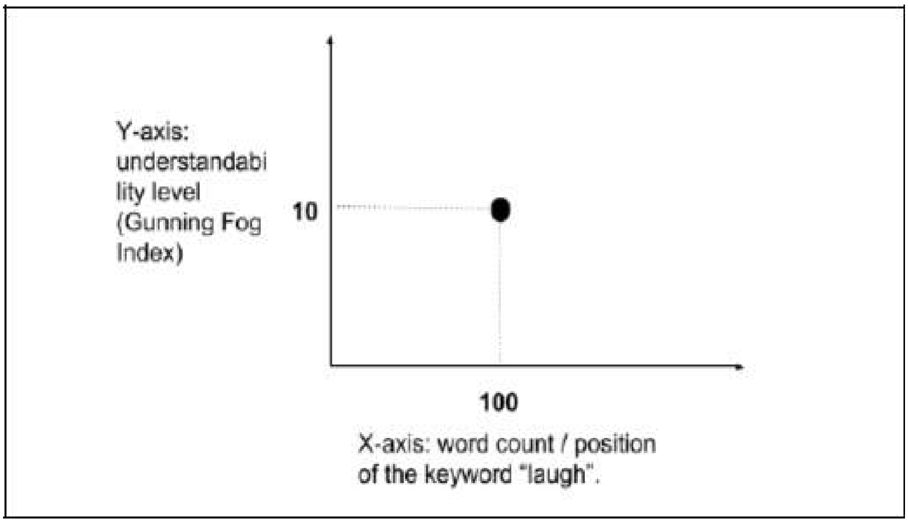

Figure 1. Plotting the audience's laughter instances. The X-axis shows the word count position of the keyword '(Laugh).' The Y-axis pertains to the value of the Gunning Fog Index for the sentences before the keyword.

4.2 Results

4.2.1 Experiment 1: Laughter frequency – popular and least popular talks

Popular talks had audience laughter on an average of 12.92 times per 15 to 20 min, while unpopular talks only had an average of 3.92 times. A Welch's t-test on the laughter frequency of popular and unpopular talks revealed that the difference was statistically significant between the two datasets ($p < 0.001$).

Audience laughter frequency in popular talks tended to vary more (M = 12.62, SD = 12.65) than in unpopular talks (M = 3.92, SD = 5.23). For instance, it was found that the highest laughter frequency for popular talks was 69 times while the lowest was 0 times. Out of 50 talks, two had zero humor usage for popular talks. On the other hand, 13 talks showed no humor usage for unpopular talks. Table 1 describes the statistics for the humor frequency in popular and unpopular talks.

Table 6. Summary of statistics for the humor frequency of TED Talks.

	N	Minimum	Maximum	M	SD
Popular talks	50.0	0.00	69.00	12.62	12.65
Unpopular talks	50.0	0.00	30.00	3.92	5.23

4.2.2 Experiment 2: Laughter placement – popular talks

The placement of laughter in the presentation timeline was calculated using the sentence position when audience laughter occurred and its frequency (see Figure 2). The study observed six occurrences and four occurrences for the same sentence position in the presentation timeline for the most popular and least popular talks, respectively. Although popular talks had more observed laughter instances than less popular talks, the placement of laughter in the presentation timeline seemed similar for both datasets. As shown in Figure 1, audience laughter was more commonly observed during the first part of the talk and gradually lessened toward the end.

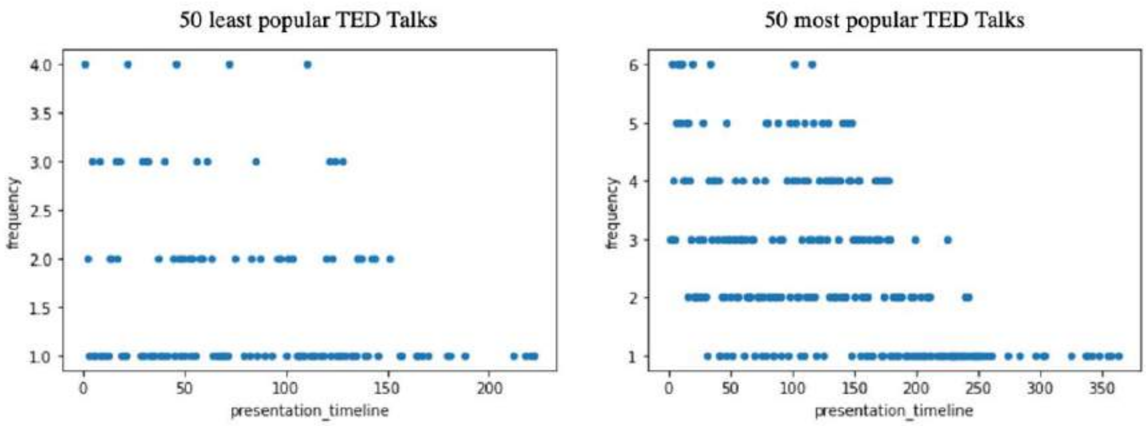

Figure 2. The frequency of audience laughter in the top 50 least popular (left) and top 50 most popular (right) TED Talks. The x-axis showed the presentation timeline or the nth position of the sentence when audience laughter occurred during the presentation. Frequency counts for each sentence's nth position are shown on the y-axis.

In Experiment 1, the findings are that for a 20-minute talk, the audience laughs an average of 13 times, and speakers use language understandable or appropriate to 9th-grade students (high school freshman) and above. During the analysis, it was observed that the scatterplots of each presentation tend to concentrate on certain parts of the timeline. To divide the presentation timeline for better pattern recognition, we used the following criteria described in Table 2.

Table 7. Division of the presentation timeline into three categories: start, middle, and end.

Percentage (%) of total word count	Category
0 to 30%	Start
31% to 70%	Middle
71% to 100%	End

Table 7 displays the criteria for dividing the presentation timeline into three parts – start, middle, and end. These sections of the presentations are determined using each presentation's word count ranges. The first zero percent (0%) to thirty percent (30%) of the total word count is the "start." The next thirty-one percent (31%) to seventy percent (70%) is the "middle." The last seventy-one percent (71%) to one hundred percent (100%) is the "end." Percentages are used instead of defined ranges for word counts since each presentation has a different total word count. Thus, although the start, middle, and end word count positions vary for each talk, the percentage ranges are the same, and comparisons can be constructed.

By analyzing the 38 most popular TED Talks, our experiment found four patterns of audience laughter frequencies. For each pattern, the study also calculated the differences in the intervals between each laugh, the position of laughter in the presentation, the Gunning Fog Index values, and the average presentation length or the total word count. Figure 3 summarizes the percentage of the four patterns. The *laughter in two categories* (34%) and *continuous* (32%) patterns were found to have the most significant shares.

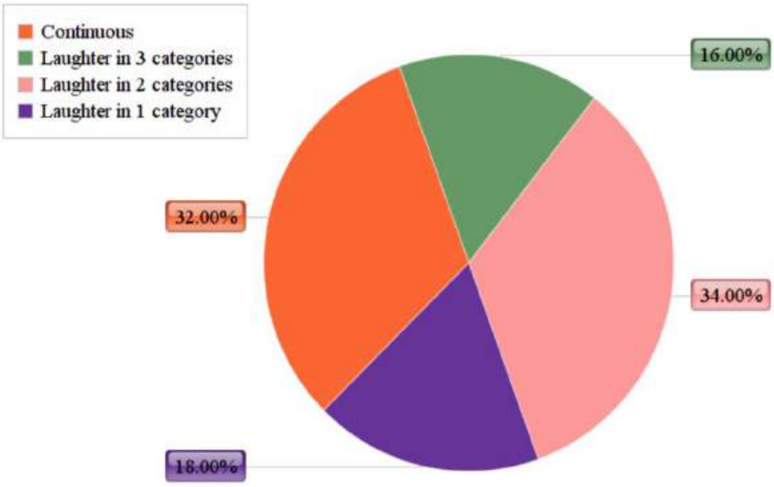

Figure 3. Patterns of audience laughter.

- *Pattern 1: Continuous laughter*

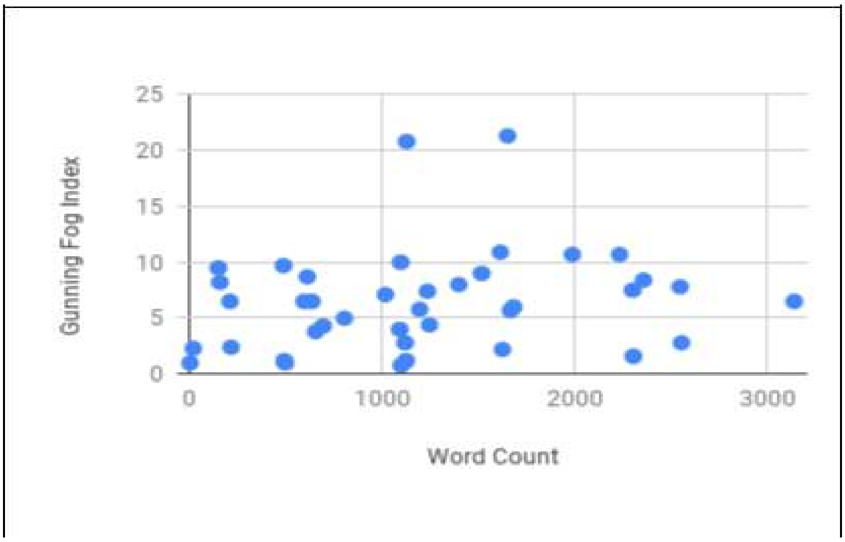

Figure 4. Scatterplot of "Do schools kill creativity" presentation by K. Robinson.

This study's first pattern has continuous occurrences of audience laughter throughout the presentation. The difference between each occurrence of laughter is very short, at 91 words, and is distributed all through the presentation. Thirty-two percent (32%) of the most popular TED Talks fall under Pattern 1. In addition, the number one most popular video on TED Talks (as of October 1, 2021), "Do schools kill creativity" by Ken Robinson, also falls under this pattern. Figure 2 shows the scatterplot for a presentation classified under Pattern 1. The y-axis shows the Gunning

Fog Index scores, and the x-axis represents word count. The average Gunning Fog Index is 9, which means that the speakers use words and sentences that could be understood by ninth-grade students (high school freshmen) and above. Finally, the mean frequency of audience laughter is 25 times for presentations about 20 minutes in length; the audiences laughed every 48 seconds on average.

- *Pattern 2: Laughter is observed at the start, middle, and end*

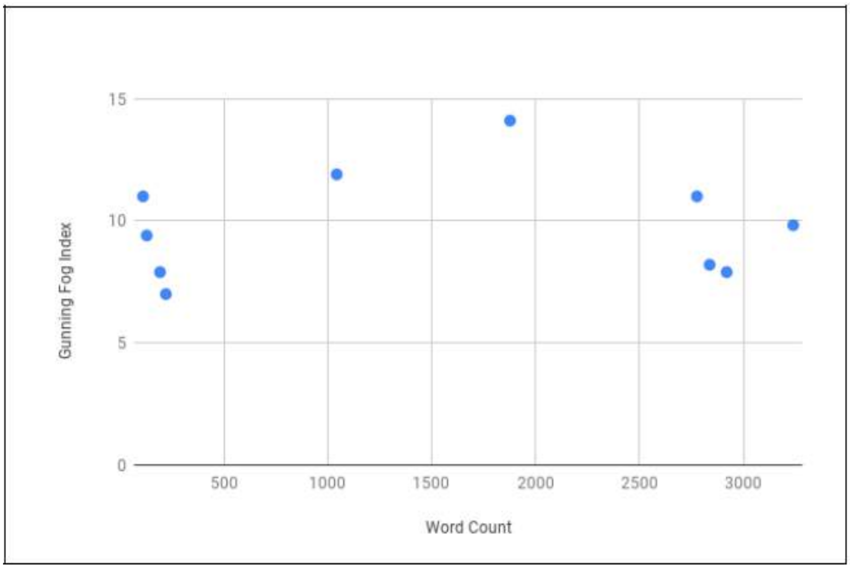

Figure 5. Scatterplot of "How to speak so that people want to listen" presentation by J. Treasure.

The second pattern that the study found in examining the video transcripts is that audience laughter is concentrated at the three main parts of the presentation: at the start, middle, and end. Unlike Pattern 1, the gaps between the occurrences of jokes from each of the three main sections of the presentation are significant, around 399 words or more. Sixteen percent (16%) of the presentations examined fall in this category. Figure 3 shows the scatterplot of the presentation titled "How to speak so that people want to listen" by J. Treasure, classified under Pattern 2. The scatterplot shows that audience laughter is somewhat affected by the text's readability level, wherein laughter occurs at points where the Gunning Fog Index is high. The presentation transcript seems to have a Gunning Fog Index of 5 to 15 with an average of 10. In Pattern 2, the average frequency of audience laughter is seven times, or laughter occurs every three minutes.

- *Pattern 3: Laughter is observed in two categories*

The third pattern observed is that audience laughter occurred at the start of the presentations and in another section of the presentation timeline. The subsequent concentration of laughter instances occurred either in the middle or towards the end of the presentation. This pattern can be broken into two categories (1) laughter observed at the start and middle and (2) laughter observed at the start and end. Thirty-four percent (34%) or most of the analyzed talks are classified under Pattern 3. The audience laughed every two minutes or nine times during the talk, and the intervals between these instances were 226 words. The Gunning Fog Index for presentations in this pattern had an average score of 9.

➢ Laughter is observed at the start and middle

Thirteen percent (13%) of the talks would have the audience laugh only at the start and middle of the presentation. Similar to Pattern 2, these presentations have a Gunning Fog Index range between 5 and 15, with an average of 9. No laughter was observed during the end of the talks.

➢ Laughter is observed at the start and end

The other variation of Pattern 3 is audience laughter focusing on the start and end of the presentation. Twenty-one percent (21%) of the presentations fall under this condition. Figure 6 shows a scatterplot of a presentation titled "The best stats you have ever seen" by H. Rosling, classified in this category. Audience laughter occurs mainly during the talk's start and end, and no laughter was observed during the middle section of the talk.

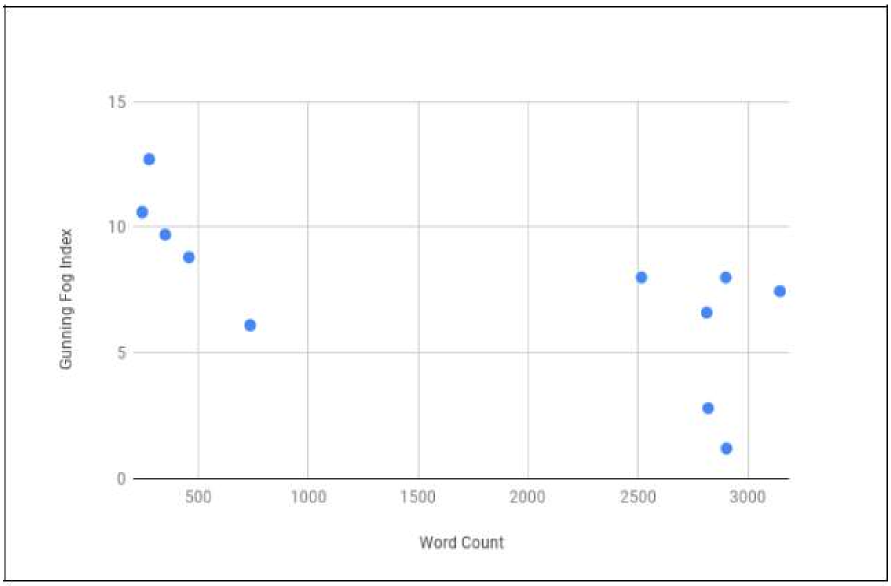

Figure 6. Scatterplot of "The best stats you have ever seen" presentation by H. Rosling.

- *Pattern 4: Laughter is observed in one category*

The last pattern makes up eighteen percent (18%) of the total presentations. The mean Gunning Fog Index is the highest in contrast with the other patterns at 11. The intervals between the laughter were 179 words. Pattern 4 has few instances of audience laughter compared to the different three patterns, with a mean of 4 times or laughter occurring every 5 minutes. Furthermore, these instances occur only at one specific presentation section, either at the start, middle, or end.

- Laughter is observed at the start

The first type of Pattern 4 has audience laughter occurring only at the presentation's start, which accounts for eight percent (8%) of the talks. The study infers that the speakers in these talks only use laughter to attract their audience's attention at the start of their presentation and keep the interest using other methods, such as gestures, videos, or asking questions, which are out of the scope this paper. Figure 7 shows the scatterplot for the presentation titled "How to make stress your friend" by K. McGonigal, where audience laughter occurred only during the start of the talk.

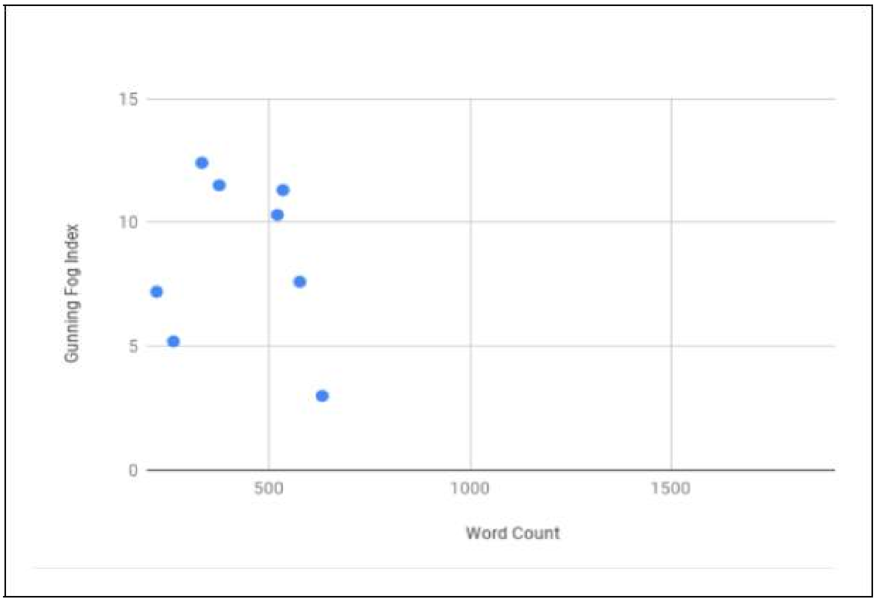

Figure 7. Scatterplot of "How to make stress your friend" presentation by K. McGonigal.

➢ Laughter is observed in the middle

The second type of Pattern 4 has audience laughter occurring only during the middle part of the presentation, and it accounts for eight percent (8%) of the total presentations examined. Audience laughter was captured from around a word count of 500 up to about 2,000, equivalent to the middle part of most TED Talks, where presentation length ranges from 1,500 words to 3,500 words.

➢ Laughter is observed at the end

The last type of Pattern 4 has audience laughter occurring only towards the end of the presentations. This is the least common of all the patterns, with only one presentation (3%) falling under this type. The audience's laughter occurred only towards the end of the presentation, starting from about the 2,000-word count. Since only one presentation falls under this classification, analysis is limited, and no comparisons are available with other similar presentations.

4.3 Discussions

The results from the investigation on the frequency of audience laughter in TED Talks showed that presenters' incorporation of laughter in their talks is significantly high (M = 12.62) as compared to the results from previous research on student laughter frequencies in educational settings (Willman, 1940; Chen & Lee, 2017; Acosta, 2016). While earlier research findings in traditional classroom settings found student laughter once every 15 minutes (Bryant et al., 1979), our research findings revealed audience laughter once every 1.58 minutes. These findings show that humor usage by speakers in TED Talks is significantly more frequent than among teachers in traditional classroom settings. Learning environments in TED Talks incorporate more laughter than traditional classroom settings do.

The popularity of TED Talks among online viewers also follows past research wherein talks with higher frequencies of humor receive higher satisfaction and popularity ratings (Bryant et al., 1980). Therefore, whether in TED Talks or non-TED settings, high frequencies of laughter are associated with high popularity among audiences. Although it was not possible to identify what might cause the high laughter frequency in this study, this topic can be another point of interest for researchers to study in the future.

This chapter also showed four (4) patterns in the audience laughter frequencies of the most popular TED Talks. We see that most popular TED talks involve audience laughter at the presentation's start. Thus, the beginning of the talk seems to affect the popularity of the TED Talks. Table 3 contains summary information on the identified four patterns and their respective data regarding average intervals between audience laughter instances, average Gunning Fog Index, average word count, the average number of audience laughter, and percentage share. From Table 8, we can observe that Pattern 1 is more used for brief and light speeches since the Gunning Fog Index average of talks that fall in this category is 8. The presentations following Pattern 1 also have very short intervals of 91 words between each laugh. The study proposes that the frequent audience laughter caused the low Gunning Fog Index. It was assumed that sentences leading to audience laughter are generally easier to understand and thus lower the overall Gunning Fog Index of the talk transcript.

Table 8. Summary of the four patterns of audience laughter.

Pattern	Description	Average intervals between audience laughter	Average Gunning Fog Index	Average word count	The average number of audience laughter	Percentage (%) of total presentations analyzed
1. Continuous	There is a continuous occurrence of audience laughter throughout the presentation	91 words	8	2560	25 times	32%
2. Observed in 3 categories	Audience laughter was observed in the three categories - start, middle, and end	399 words	10	3164	7 times	16%
3. Observed in 2 categories	Audience laughter was observed in 2 categories. Either (1) at the start and middle or (2) at the start and end	226 words	9	2593	9 times	34%
4. Observed in 1 category	Audience laughter was observed in only one category, either at the (1) start, (2) middle, or (3) end	179 words	11	2243	4 times	18%

On the other hand, presentations under Pattern 2 have the highest differences in the intervals between times when the audience laughs. The huge interval mean might be caused by the concentration of jokes or punchlines by parts. The jokes are made closely in a specific part of the presentation, like the start, middle, or end. For instance, intervals of audience laughter made at the start of the presentation with laughter instances made at the end of the presentation would be higher, hence the higher interval average. Pattern 2 is the most common out of all other identified patterns.

For Pattern 3, intervals between jokes have an average of 226 words, a Gunning Fog Index of 9 that is the same as the 9 average scores for the 38 TED Talks combined, and presentation length is about 2,593 words. Lastly, Pattern 4 tends to have the most complex presentations with a Gunning Fog Index average of 11 and the shortest presentations with an average presentation length of 2,243 words.

Table 8 also shows the average number of instances the audience laughed during the presentation. Pattern 1 has the highest frequency of laughs, and Pattern 4 has the least. The study results show that audience laughter can lower the Gunning Fog Index or make the text more understandable. Pattern 1 presentations with the highest mean laughter frequencies have a much lower Gunning Fog Score of 8 than presentations in Pattern 4, with the least mean laughter frequency, with a mean Gunning Fog Score of 11. Thus, this research can infer that making jokes increases understandability or lessens the Gunning Fog Score.

This experiment has several limitations. First, the data consisted of only 38 presentations, and larger sample size could show more results or patterns. Next, the analyzed presentations are limited to those conducted in English. Therefore, future studies could compare patterns in different languages or cultures. Another limitation was that audience laughter in this study results from group laughter, and there is no way to determine if all or just a few were laughing. Since a joke may be funny to one person, it may not be the case for another. In this study, the word count was used to represent the time since the periods of silence, pauses, and laughter could affect the analysis. Other researchers might be interested in analyzing the pattern of the audience laughter using time, not word counts, for comparisons.

Lastly, the presentation timeline was divided into the start, middle, and end sections. This method and the percentage ranges of word count to split the presentation timeline may have contained some bias on the researcher's part in categorizing the patterns. Future works can opt to provide alternative ways of dividing the presentation timeline. The relationship and possible correlation between the number of jokes and the Gunning Fog Index score will be studied in the future. Other measures of readability scores or methods for calculating text understandability will also be used and compared with the results of the Gunning Fog Index.

This chapter showed several patterns in which the audience laughs in popular presentations. The most popular patterns are having continuous laughter throughout the talk and incorporating laughter only in two presentation sections, the start and the middle and the start and the end. Although this chapter guides laughter placement, speakers should be free to pick any pattern or style which suits them and their audience. Since some speakers may not be comfortable incorporating too much laughter in their presentations, they can contain laughter at least during the start of the lesson, as observed in this research; having audience laughter at the start is commonly observed in popular presentations.

This chapter is a slightly modified version of "A study on instructional humor: How much humor is used in presentations?" published in Behavioral Sciences. Vol.12 (1), 7 and reproduced here with the copyright holder's permission.

Chapter 5

Computational Linguistics: TED Talks and non-TED humor

Are there any TED-specific characteristics in the way speakers make their audience laugh? This chapter focuses on the research question, "How different or similar are the linguistic features of humorous sentences used in TED Talks with non-TED content?". To answer this, the humorous sentences were extracted from the transcripts of TED Talks, and the linguistic features such as word frequencies, parts of speech, readability score, and sentiment analysis were analyzed. Lastly, these results were compared with non-TED content, such as user-submitted one-liner jokes.

5.1 Methods

In this experiment, two corpora were used: TED Talks and user-submitted jokes from stupidstuff.org. For the TED Talks, the transcripts of 2000 talks were extracted. After scraping the website, two CSV files were created for each corpus. The talks were split into sentences using the Stanza module (formerly the Stanford Core NLP) (Qi et al., 2020), then labeled sentences containing or immediately followed by the special markup "Laughter" in Python to get the sentences containing humor from the TED Talks transcripts. After data cleaning and processing, 8906 humorous sentences were obtained from the TED Talks dataset. For stupidstuff.org, the dataset contained transcripts of 3200 user-submitted jokes. Finally, using NLP techniques and descriptive and inferential statistics, several linguistic features were looked at to compare the humorous sentences from the two corpora.

- *Word Frequency, Bigrams, and Trigrams*

Previous works identified that humor has a variety of functions, both positive and negative (Booth-Butterfield et al., 2007). Therefore, it is vital to see whether there is a difference between the choice of words in jokes used in TED Talks and non-TED jokes. To get the word frequency or the most frequent words appearing in our corpora and the most popular bigrams and trigrams of humorous sentences, Python's open-source NLTK (Natural Language Toolkit) library (Loper & Bird, 2002) was utilized.

- *POS (Part of Speech)*

Works in computational humor research found that humorous messages use personal nouns and proper nouns, such as when referring to human-related scenarios (Michalcea & Pullman, 2007; Yang et al., 2015; Zhang & Liu, 2014). To see whether the humorous sentences in our dataset follow this theory, an open-source library, TextBlob (Loria, 2018), was used in Python for POS tagging.

- *Readability Score*

The study used the Flesch reading ease and the Gunning Fog Index to calculate the readability of the humorous sentences. The Flesch reading ease scores range from 0 to 100, with 0 being extremely difficult and 100 being very easy to read (Kincaid et al., 1975). On the other hand, the Gunning Fog Index rates text from 6 to 17, and each of these scores has an equivalent educational level that determines the text's difficulty (Gunning, 1969). For example, a text with a Gunning Fog Index of 6 can be read by sixth-grade students, while a score of 17 can be read by college graduates (Gunning, 1969). The analysis used the open-source library TextStat (Diniz, 2005) and descriptive and inferential statistics in Python to conduct a readability score analysis.

- *Sentiment Analysis*

Research on the types of humor explains that the sentiment of the humorous messages can negatively or positively affect the listener (Provine, 2001; Kane et al., 1977). For instance, humorous sentences having a negative feeling can lower students' learning performance (Provine, 2001; Kane et al., 1977). Thus, it is essential to conduct sentiment analysis on our dataset. The study used the open-source library TextBlob (Loria, 2018) in Python to compute the polarity or sentiment of our dataset's humorous sentences.

5.2 Results

The results from NLP techniques such as calculation of word frequencies, *n*-grams, POS tagging, readability scores, and sentiment analysis applied to TED Talks and stupidstuff.org corpora are described in this section.

The top 10 most frequently used words for the TED Talks and stupidstuff.org datasets are described in Figure 8. The most common word for humorous sentences in TED Talks was "like," and it was "said" for studpidstuff.org. The two datasets share some similarities in word frequencies. For example, the words "one," "said," "say," and "get" both appeared in the top 10 most frequently occurring words for both datasets.

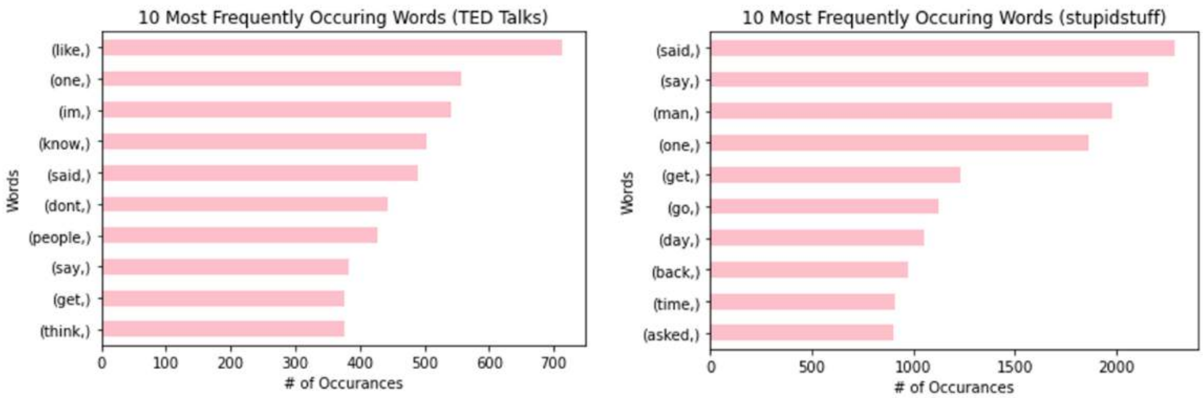

Figure 8. The 10 most frequently occurring words for humorous sentences in TED Talks (left) and user-submitted jokes from stupidstuff.org (right).

Next, the study looked at the most frequently used bigrams or two-word combinations. In Figure 9, we see that "I'm, going" and "one day" were the most common bigrams for TED Talks and Stupidstuff.org datasets, respectively. Notably, the bigram "don't know" appeared in both datasets.

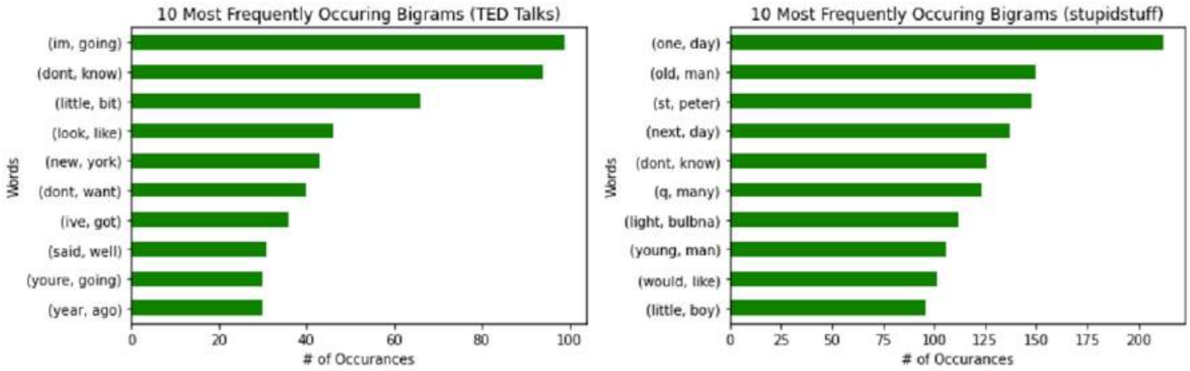

Figure 9. The 10 most frequently occurring bigrams for humorous sentences in TED Talks (left) and user-submitted jokes from stupidstuff.org (right).

Finally, the research looked at the most common trigrams (see Figure 10). "New York, City" was the most frequently used trigram in the TED Talks dataset, and it was "take, change, light" for the stupidstuff.org dataset. Results found no similarities between the two datasets' most frequently used trigrams.

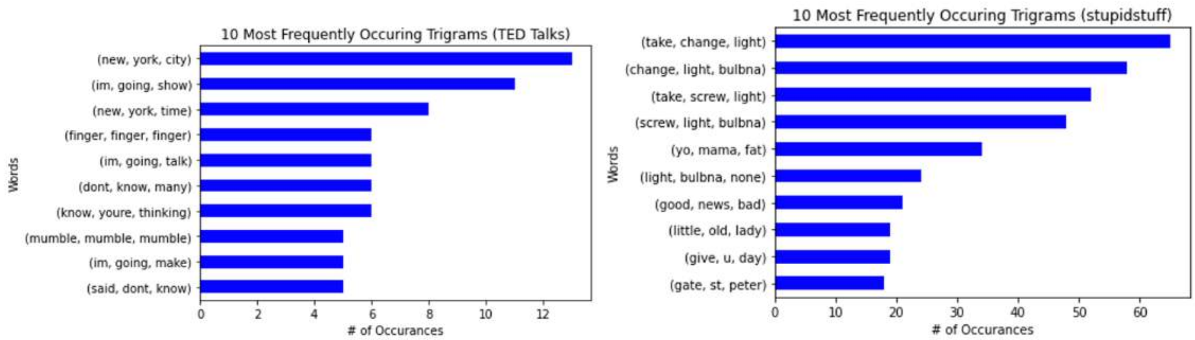

Figure 10. The 10 most frequently occurring trigrams for humorous sentences in TED Talks (left) and user-submitted jokes from stupidstuff.org (right).

We observed a high usage of possessive ending (POS) and proper nouns in singular form (NNP) for both datasets. This result supports previous works that state that humorous messages tend to use possessive forms and adequate nouns (Booth-Butterfield et al., 2007; Michalcea & Pulman, 2007; Yang et al., 2015). Figure 11 below contains information on the two datasets' top 10 most frequently used POS. Strikingly, the top 10 commonly used POS were similar for the two datasets. For example, the POS verbs in gerund or present participle form and verbs in the past tense form were frequently observed.

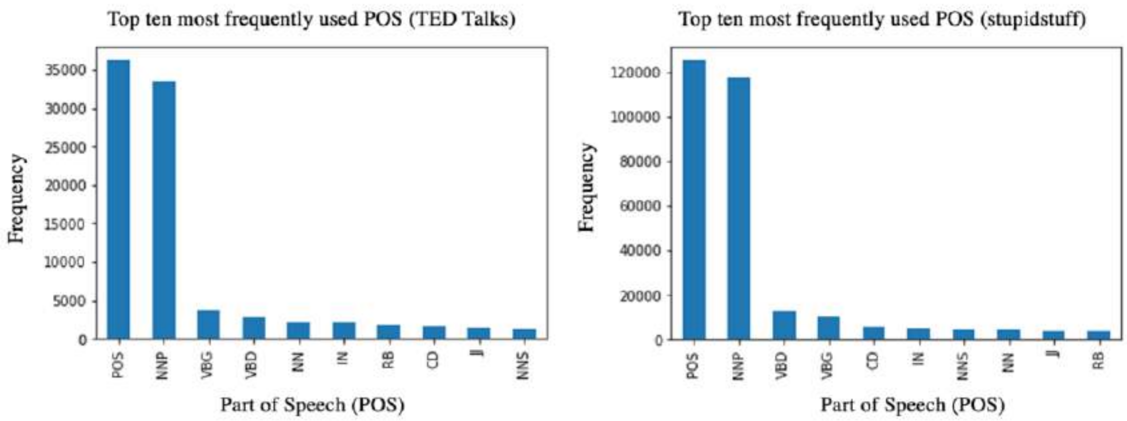

Figure 11. The 10 most frequently occurring POS for humorous sentences in TED Talks (left) and jokes from stupidstuff.org (right). Legend on POS tag definitions: POS (possessive ending), NNP (proper noun, singular), VBG (verb, gerund/present participle), VBD (verb, past tense), NN (noun, singular), IN (preposition/subordinating conjunction), RB (adverb), CD (cardinal digit), JJ (adjective), NNS (proper noun, plural).

Using the Flesch reading ease score, results showed that humorous sentences for both datasets tended to have scores from 60 to 100, with the peak at 80 and an average of 72–74. The results mean that the humorous sentences range from reasonably difficult to very easy to read. Humorous sentences from the TED Talks dataset (M = 73.89, SD = 17.32) were slightly easier to read and had minor variance than user-submitted jokes from stupidstuff.org (M = 72.45, SD = 18.88). Table 9 summarizes the results of the analysis. Welch's t-test on the readability scores using the Flesch reading ease shows that they were statistically significant ($p < 0.001$).

Table 9. Summary of statistics for the readability scores using the Flesch reading ease score.

	N	Minimum	Maximum	M	SD
TED Talks	7348.00	1.09	99.91	73.89	17.32
User-submitted jokes	2839.00	0.43	99.94	72.45	18.88

The number of samples used in this analysis removed outliers or talks that had readability scores out of the range of the scores determined by the Flesch reading ease score (see Figure 12).

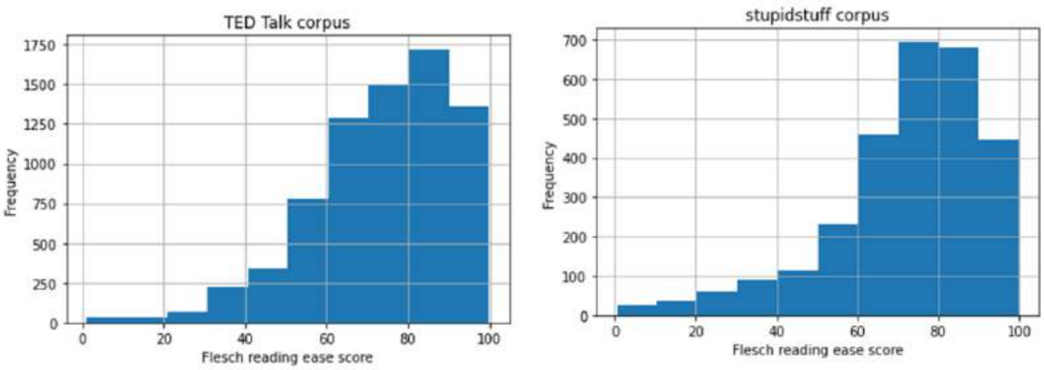

Figure 12. Histogram of readability scores for humorous sentences in TED Talks (left) and jokes from stupidstuff.org (right) using the Flesch reading ease method.

The study also looked at the Gunning Fog Index for both datasets to further assess the readability of the humorous sentences. Outliers or talks that had readability scores out of range of the scores determined by the Gunning Fog Index were removed in this analysis. Table 10 describes the results of the statistical tests. A Welch's t-test on the readability scores using the Gunning Fog Index revealed that the difference was statistically significant ($p < 0.001$).

Table 10. Summary of statistics for readability scores using the Gunning Fog Index.

	N	Minimum	Maximum	M	SD
TED Talks	5116.00	6.22	16.96	10.55	2.65
User-submitted jokes	2094.00	6.01	16.98	10.19	2.82

Figure 13 describes the detailed results of the Gunning Fog Index assessment. The stupidstuff.org dataset (M = 10.19, SD = 2.82) tended to have slightly more variation in scores than the TED Talks dataset (M = 10.55, SD = 2.65). Nevertheless, both datasets returned scores with an average of 10, meaning lower grade levels can comprehend the sentences containing humor.

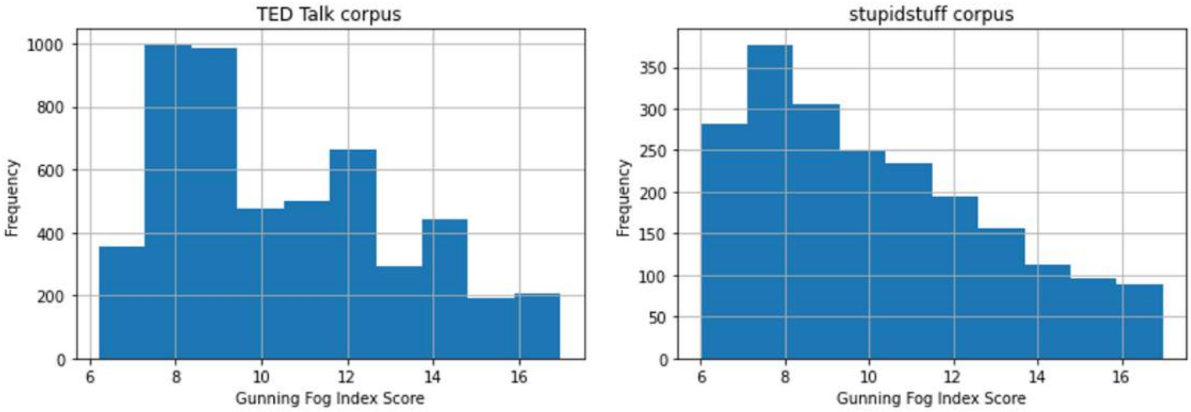

Figure 13. Histogram of readability scores for humorous sentences in TED Talks (left) and jokes from stupidstuff.org (right) using the Gunning Fog Index method. The score ranges from 6 (can be understood by sixth-grade students) to 17 (comprehensible to college graduate students).

Figure 14 shows the histogram of the polarity of humorous sentences for the two datasets. We can observe that humorous sentences for both datasets returned a neutral sentiment with an average of 0.07 and 0.06 polarity for TED Talks and stupidstuff.org, respectively. Negative scores imply a negative emotion, while positive scores indicate positive feelings, and near-zero scores usually express a neutral sentiment.

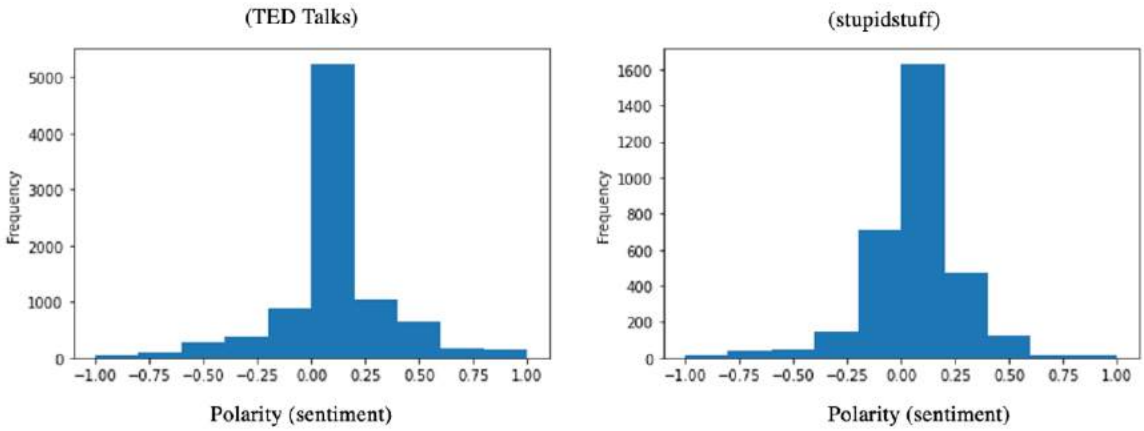

Figure 14. Histogram of sentiment for humorous sentences in TED Talks (left) and jokes from stupidstuff.org (right).

A Welch's t-test on the sentiment scores of the two datasets revealed that the difference was statistically significant (p = 0.01). Table 11 summarizes the results of the statistical tests on the sentiment scores. The observations from the sentiment analysis of sentences containing humor in TED Talks (M = 0.07, SD = 0.27) and user-submitted jokes from stupidstuff.org (M = 0.06, SD = 0.21) showed that the two were very similar.

Table 11. Summary of statistics for sentiment analysis.

	N	Minimum	Maximum	M	SD
TED Talks	8906.00	−1.00	1.00	0.07	0.27
User-submitted jokes	3200.00	−1.00	1.00	0.06	0.21

5.3 Discussions

The comparison between the linguistic features of jokes in TED Talks and user-submitted jokes provided several intriguing results. First, there seemed to be no difference between the word usage used in presentations and that used for other purposes in terms of word frequencies. The findings support past studies wherein some words were more commonly used in humorous contexts, such as when referencing human-related scenarios (Booth-Butterfield et al., 2007). In our results, words corresponding to human-centered scenarios such as "I'm," "people," and "man" are common in both cases. Similarly, previous studies suggest humorous sentences use more possessive pronouns and nouns (Booth-Butterfield et al., 2007; Michalcea & Pulman, 2007; Yang et al., 2015). The results from POS tagging are also in line with past literature since POS (possessive ending) and NNP (proper noun, singular) were the most frequently occurring POS for the TED Talk jokes and user-submitted jokes.

This research further supports describing humorous sentences as human-centric and focusing on personal opinions, as observed in previous studies (Michalcea & Pullman, 2007; Yang et al., 2015; Zhang & Liu, 2014). These results are also beneficial to using NLP for building systems for humor recognition for machines since we can devise algorithms that take the linguistic components of sentences as features to recognize the humor in sentences automatically. Furthermore, the methodology of past works using words and pronouns as features for automatic humor recognition in machines [Chen & Lee, 2017; Acosta, 2016; Taylor & Mazlack, 2004; Mihalcea & Strapparava, 2006] is also supported and validated through our research results.

We can observe a slight difference in scores from the readability scores of TED Talks jokes and user-submitted jokes when using different methods for calculating the readability. Using the Flesch–Kincaid reading ease method (Kincaid et al., 1975), TED Talks jokes had a higher mean, making them easier to understand. However, user-submitted jokes were easier to comprehend when using the Gunning Fog Index (Gunning, 1969). Only two methods for calculating the readability score were used in this research. Therefore, other researchers might apply other readability scoring methods to obtain comparable results.

Lastly, it was expected to see more negative sentiment for user-submitted jokes and more positive emotion for TED Talk jokes in terms of sentiment analysis. However, both returned scores leaned more toward a neutral view. It was expected to have more positive sentiment for TED Talk jokes since previous research suggests that humor used for education should contain positivity rather than negative feelings to create a positive learning environment (Banas et al., 2011). Likewise, it was also expected to see more negative sentiment in user-submitted jokes since past humor research studies showed that humor frequently uses negative words, adult slang, and swear words (Michalcea & Pulman, 2007). Perhaps, the methodology used for calculating the sentiment of the humorous sentences might not have been accurate enough, leading to neutrality. Since humor contains incongruity and ambiguity (Berlyne, 1960; Wanzer & Frymier, 2010), the algorithm used might not have detected the sentiment correctly. In future research, better algorithms and methods for sentiment analysis are recommended for getting more accurate results.

This chapter is a slightly modified version of "A study on instructional humor: How much humor is used in presentations?" published in Behavioral Sciences. Vol.12 (1), 7 and reproduced here with the copyright holder's permission.

Chapter 6

Overall Discussion

In this study, four research questions were investigated.

- **RQ 1.** How often is audience laughter in TED Talks? Is there a difference between audience laughter occurrences between popular and less popular presentations?
- **H 1-1.** Audience laughter is used very frequently.
- **H 1-2**. The frequency of audience laughter affects the popularity of the TED Talks.

The research question was designed as exploratory for assessing audience laughter frequencies in TED Talks, and it also compared audience laughter frequencies between the most popular and least popular presentations. The study applied text analysis to examine the audience laughter frequencies in the transcripts of TED Talks. The results showed high levels of audience laughter frequencies in TED Talks as hypothesis 1-1, and that popular talks have higher laughter frequencies than less popular talks as hypothesis 1-2. The difference between the audience laughter frequencies between popular and least popular talks was statistically significant. Therefore, there is a relationship between the popularity of TED Talks among online viewers and the frequency of audience laughter. Due to the time spent on this experiment, the study could not analyze more talks and was limited to the most popular and least popular presentations. Further research can examine this relationship by using more data and including more presentations, not only the popular and least popular talks.

- **RQ 2.** How is audience laughter placed in the presentation timeline?
- **H 2-1.** Humor is placed at the start of the presentations since this placement is best

considering the cognitive load burden for the audience.

- **H 2-2.** Humor is placed in the middle of the presentations to serve as a break.
- **H 2-3.** Humor is placed at the end of the presentations to increase the positive experience of the audience.

It was observed that audience laughter is mainly found at the start of presentations. While audience laughter was found in various parts of the talk (beginning, middle, and end), all identified patterns of audience laughter placement contained audience laughter instances at the start of the presentations. While it was not able to determine the cause of why audience laughter occurs due to the nature of the experiment, wherein the audience or the speakers in the TED Talks cannot be directly interviewed, this observation can be a future direction for research. Although the hypotheses were not statistically verified, the study was able to show that there is a potential for further research on this topic. It is recommended to increase the number of talks or have opportunities to conduct surveys with the audience and speakers in the TED Talks to generate better research findings.

- **RQ 3.** How different or similar is audience laughter in TED Talks from student laughter in traditional classroom settings?
- **H 3-1.** Audience laughter in TED Talks is more frequent.
- **H 3-2**. Educators and presenters who are more popular, experienced, and credible evoke audience laughter more frequently.

Comparing the results of audience laughter frequency in TED Talks with findings from previous studies in the educational context in traditional classroom settings, it was found that audience laughter frequencies in TED Talks are significantly higher. In traditional classroom settings, for a 50-minute lecture, average audience laughter was observed every 15 minutes. While in TED Talks, audience laughter was observed every 1.5 minutes for popular presentations. While we could not statistically measure the significance between the means, the significant difference tells us that TED Talks presentations are very different from traditional classroom settings regarding incorporating humor. It was observed that TED Talks tend to contain more audience laughter, making them more like entertainment media than traditional educational context. The study recommends that audience comprehension should be examined for future research if the high level of humor incorporation helps make people understand the content of the talks and not only their level of satisfaction or experience.

On the other hand, the study found that the popularity of the TED Talks is somehow affected or linked with the audience's laughter frequencies. Popular talks tend to have higher audience laughter frequencies. This observation can be connected with previous studies in education wherein students give a higher rating and level of satisfaction to lectures wherein the teacher frequently incorporates humor.

- **RQ 4.** How different or similar are the linguistic features of humorous sentences used in TED Talks with non-TED content?
- **H 4-1.** There is no difference in the linguistic features.

The findings show that the linguistic properties such as word frequencies, bigrams, trigrams, sentiment, readability scores, and parts of speech of jokes in TED Talks and user-submitted jokes are similar. This observation is significant to humor computing research, and it allows us to generalize jokes' linguistic characteristics and features to create systems that accurately detect, generate, and predict humor. This result also allows us to use linguistic properties such as word frequencies, sentiment, parts of speech, and readability scores as features in creating algorithms and models to predict audience laughter in presentations. Since there are no significant differences in the linguistic properties, we can also apply the prediction system to TED Talks and other non-TED presentations.

The study proposes models for creating systems in humor computing through these four research questions. For example, in building robots and virtual agents that have personalities that can generate jokes, it is recommended that humor should be placed at the start of presentations or conversations. Likewise, we recommend a high level of humor incorporation to have high levels of audience satisfaction and rating for creating educational or entertainment content. Lastly, in designing systems for the generation, detection, and prediction of jokes or audience laughter, we recommend including linguistic properties such as audience laughter frequency, audience laughter placement pattern, speaker popularity, word frequencies (unigrams, bigrams, and trigrams), parts of speech, sentiment, and readability scores as features to be used in machine learning models and algorithms.

6.1 Contribution to Human Informatics

We conducted this study to contribute to human informatics. Human informatics can be described as a field wherein we solve problems concerning human activities using computational techniques or computers. This study is to empower people in presentations or speeches through the application of computing.

6.2 Limitations

The research was limited to analyzing data from transcripts of TED Talks and user-submitted jokes. As it could not directly conduct surveys or interviews with the audience or speakers in the analyzed TED Talks, it could not measure their actual level of satisfaction, comprehension, and thoughts on humor frequency usage. Since the audience's laughter is a group reaction, it cannot assess individual differences in response to the speakers' jokes. Likewise, it can also not determine whether the audience's laughter was caused by an intended joke used by the speaker or caused by other unintentional situations or accidents.

Due to limited resources, the study was unable to include more data on analyzing the differences in the audience laughter frequencies and talk popularity and limited the data to 50 most popular and 50 least popular. It recommends including talks regardless of their popularity ranking to formulate better conclusions for future research.

Chapter 7

Conclusions

Research Objectives. This study aimed to explore the quantitative features of audience laughter and the linguistic properties of jokes in TED Talks. This research suggested analyzing the transcripts of TED Talks using computational techniques such as computational linguistics and natural language processing. The study compared quantitative features of audience laughter and linguistic properties between TED Talks and non-TED content such as lectures in traditional classroom settings and user-submitted jokes.

Research Results. This research explored the quantitative features of audience laughter and linguistic properties of jokes in TED Talks through four research questions. RQ 1 of this study was to explore audience laughter frequencies in TED Talks. Experiments on analyzing the transcripts of TED Talks and measuring audience laughter instances through the special markup "Laughter" found in the transcripts were conducted. Then, statistical tests were performed to measure the differences between audience laughter frequencies between popular and least popular presentations. The study discovered that popular presentations have more audience laughter than most minor popular presentations. To find out if there are any patterns of audience laughter, RQ 2 was investigated. The study analyzed the transcripts of TED Talks and plotted the audience laughter instances. The findings show that audience laughter patterns vary among presentations. However, audience laughter was commonly observed during the start of the talks. RQ 3 of this research was to see if there are any TED-specific characteristics in terms of audience laughter frequencies. To investigate, it compared the results of our experiment with previous studies measuring student laughter instances and humor frequency usage of teachers in traditional classroom settings. Results show that TED talks incorporate higher levels of audience laughter than traditional classroom lectures. However, popularity in TED Talks is affected similarly to lectures in traditional classroom settings, wherein higher levels of humor frequency lead to higher popularity ratings. Lastly, to study the linguistic properties of jokes used in TED Talks, RQ 4 was investigated. The study detected and analyzed the jokes used in TED Talks and compared the linguistic properties with non-TED jokes (user-submitted jokes). Findings show that the linguistic properties of jokes in TED talks and user-submitted jokes are similar. The study recommends that these linguistic properties be applied as features in machine learning algorithms and models for building systems in recognition, detection, generation, and prediction of jokes or audience laughter.

Future Work. In this research, it was proposed that linguistic properties of jokes such as audience laughter frequency, audience laughter placement pattern, the popularity of speakers, word frequencies (unigrams, bigrams, and trigrams), parts of speech, sentiment, and readability scores be applied as features in building machine learning models for generation, detection, recognition, and prediction of jokes and audience laughter. The research aims to create an audience laughter prediction system using the proposed linguistic features in future works. The audience laughter prediction system is aimed to be used to predict audience laughter in TED Talks and other non-TED presentations or speeches.

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About the author

Vera Paola R. Shoda is a researcher in social informatics, behavioral sciences, and educational technology. She received a B.S. degree in Business Administration from the University of the Philippines (Diliman campus), Philippines, in 2015 and an M.B.A degree in International Project Management from Kyoto University, Japan, in 2018. She currently works as an Assistant Professor at the Research Institute for Economics and Business Administration (RIEB) and the Center for Computational Social Sciences (CCSS) of Kobe University, Japan. She hopes to empower people through research in technology applications and computational techniques for solving social problems.

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