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**Analysing the Role of
Pauses in Literary Text
Using Deep Learning and
Emotion Analysis**

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To my mother, Yunyi

Abstract

This study analyses the role of pauses in Samuel Beckett's *Waiting for Godot* using deep learning-based emotion analysis. Previous emotion analysis studies have mainly focused on explicit emotional expressions, but Beckett's work is distinctive in that emotions are not directly revealed, and pause plays a crucial role in the text. To address this, the study proposes a new approach to analyse the role of pauses on emotions in literary texts. In this study, the dialogues of literary texts were converted into a form of structured data, and multiple emotion classification was performed using the ELECTRA deep learning model. The results indicate that pauses have a tendency to keep emotions in their existing state and thus play a role in regulating the emotional balance of the tragicomedy genre. Furthermore, it was found that pauses regulate the emotional rhythm of the play, maintaining neutrality and moderating extreme emotional changes. These results provide a new perspective through the deep learning emotion analysis on the interpretation of pauses as emotional and structural mechanisms in literary studies, rather than as simple spaces between lines of dialogue. Therefore, this study is significant for quantitatively assessing the emotional impact of non-linguistic elements in literary analysis using deep learning techniques and highlights the need for future emotion analysis models to consider factors such as pauses. Lastly, this study contributes to the methodological expansion of emotion analysis research and suggests possibilities for the convergence of literary studies and digital humanities.

Keywords Deep Learning, Emotion Analysis, Literary Analysis, Samuel Beckett, Digital Humanities

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1 Introduction

*What has a positive existence is useful for adaptation,
but what does not exist is essential for true usefulness.*

Laozi, *Tao Te Ching*, Chapter 11

1.1 An Empty Space between Text and Emotion

From papyrus epistle in B.C. to sending text messages on smartphones today, humans have been using text since ancient times not only to transmit information but also to express emotions. However, with the increasing frequency of emotional communication through text in modern society, the role of invisible, non-linguistic details is becoming increasingly important. In particular, pauses in dialogue and conversations are not just spaces, but they are an important mechanism for emotion [1]. We read hesitation in the pause that follows the other person's texts and detect unseen emotions through the gap between the arrival of messages. It's a concept that has been discussed in a variety of domains, from ancient philosophy to modern linguistics, psychology, and more recently, artificial intelligence research.

The earliest scholars to explore the relationship between emotion and text include Aristotle and William James. Aristotle, in his *Rhetoric*, identified *pathos*, which is emotion, as a key element of persuasion and argued that emotions can be enhanced through linguistic expression [2]. This suggests that emotions do not simply arise within the individual but are shaped by the process of being channelled through a text and influencing the recipient. On the other hand, William James explained emotion as a complex process that combines physical response and verbal expression [3]. This means that emotions are constructed experientially in the process of reading or listening to a text as well as in its textual elements. Some of the scholars who have emphasised that the expression of emotion is not just at the level of words but can be enhanced by combining it with non-linguistic elements include Roman Jakobson. Jakobson stressed the emotional function of language among its many functions, and identified elements such as intonation, rhyme, and rhythm as important ways of conveying emotion [4].

In these discussions, pauses function as a unique mode of expression that forms the boundary between linguistic and non-linguistic elements within a text. Erving Goffman suggested that pauses in dialogue serve to regulate flow, emphasise or conceal emotions [5]. Maurice Poyatos explained that silence is not just a gap, but an active mode of communication that creates emotional tension and implies meaning [1]. This demonstrates that pause is not merely an absence, but act as a means to regulate the intensity of emotions and extend meaning. In particular, explicitly marked pauses in literary texts are not just linguistic interruptions. It provides an opportunity to contemplate the silence through the empty spaces between words while visually revealing what cannot be expressed through language [6]. Therefore, in this study, we focus on how pauses in literary texts play a role through deep learning and emotion analysis.

1.2 Research Objectives

This study aims to analyse the role of pauses in dialogue based on literary texts. Literary texts are an invaluable material for observing human emotions and behaviour. Literature-based texts reflect social and psychological factors in a more refined form than typical everyday dialogue, making them suitable for analysing complexly structured human emotions [1]. In particular, play is a useful genre for emotion analysis research, as it contains both colloquial features and scripted narrative. This gives a glimpse into the structure and pattern of pauses intended by the author and provides an insight into the nature and function of pauses through literary texts[7]. Therefore, analysing the impact of pauses on emotional expression and structural composition in literary texts can be an academically relevant research topic.

Recent advances in *natural language processing* (NLP) have made it possible to perform enhanced emotion analysis of literary texts. For example, large-scale emotion classification datasets such as the GoEmotions dataset have emerged, enabling multilabel emotion analysis [8]. Moreover, the emergence of deep learning-based bidirectional structure-enforced NLP models such as *Bidirectional Encoder Representations from Transformers* (BERT) and *Efficiently Learning an Encoder that Classifies Token Replacements Accurately* (ELECTRA) has provided a way to analyse emotions in literary works in multiple dimensions [9][10]. These technological advances offer new possibilities for analysing the non-linguistic elements of literary texts.

In particular, Samuel Beckett is one of the most prominent playwrights to make dramatic use of pauses[7]. In his plays, the pause is not just a simple stop, but has a philosophical meaning that expands the space between thought and feeling and is a key device that dominates the mood and emotion of the entire text [11]. His play, *Waiting for Godot*, has a structure that uses pauses in a balanced dialogue between two main characters, making it suitable for emotion analysis research. Thus, this study aims

to analyse the role of pauses in relation to emotions in the text by quantitatively analysing the dialogue of *Waiting for Godot*, and to explore the significance of non-linguistic elements in the analysis of emotions in literary texts.

1.3 Structure of the Thesis

This paper analyses the role of pause in *Waiting for Godot* using deep learning and emotion analysis, with the discussion structured as follows.

- **Chapter 2. Related Work:** reviews prior work in the field of emotion analysis research and explores how existing emotion analysis has evolved. In particular, it considers applications of emotion analysis in literary texts and explains how our approach differs from previous research.
- **Chapter 3. Samuel Beckett and His Works:** examines the meaning of pause and silence in Samuel Beckett's work, both in his own words and in the analyses of critics. Following this, it examines the textual features and emotional structure of his play *Waiting for Godot* and discusses why it is a suitable study for this emotion analysis study. It also analyses the ways in which pause is used as a key device that governs the mood and emotion of the text as a whole.
- **Chapter 4. Methodology:** describes the research methodology in detail. It covers data preprocessing, emotion analysis techniques using deep learning models, model training, and visual representation of analysis results. Specifically, it details the process of training an emotion analysis model using the GoEmotions dataset and how to extract emotions from dialogue in *Waiting for Godot*.

- **Chapter 5. Results:** the key findings from the emotion analysis are presented. In this chapter, the overall emotions of the main characters are analysed, the impact of pauses on emotional changes is quantitatively assessed, and the impact is visually illustrated using data visualisation.
- **Chapter 6. Discussion:** discusses the role of pauses in literary texts in relation to emotion based on the results of the analysis. It compares and analyses through the perspectives of existing literary criticism and emotion analysis research, and assesses whether this study can contribute to the methodological expansion of emotion analysis and the interpretation of non-linguistic elements in studies.
- **Chapter 7. Conclusions:** summarises the main findings of the study, discusses the limitations of the study and suggests directions for future research. In particular, this study explores how emotion analysis techniques can be developed within literary studies and examines the potential for their application across a broader range of domains in the future. Furthermore, it considers whether emotion analysis based on literary works can be extended to real human data.

2 Related work

This chapter describes the evolution of emotion analysis research and its application in literary texts. In Section 2.1, we describe how emotion analysis has evolved from early sentiment dictionary-based approaches to sophisticated analyses using machine learning and deep learning, with examples from many domains, including business, psychology, social media, healthcare, and economics. Next, in Section 2.2, we focus on applications of emotion analysis to literary studies, examining studies that analyse emotional flow and textual structure in literary texts such as Shakespearean plays, traditional fairy tales, and full-length novels. In doing so, it discusses how the analysis of emotional flow and character relationships in literary texts has evolved in emotion analysis study.

2.1 Previous Work on Emotion Analysis

Emotion analysis can be defined as a technique for identifying and classifying different emotional states within a text, for example joy, sadness, anger, fear, and so on. The study of emotion analysis originated from that sentiment analysis. Also known as sentiment analysis or opinion mining, this field of study focuses specifically on the analysis of opinion that express or imply positive or negative emotions. The field of sentiment analysis has grown rapidly since 2000, when the development of the internet

and big data led to the creation of opinion data [12]. Initial research areas were business domains such as competitive analysis, marketing analysis and risk management [13]. However, the research has been widely open to almost every domain since its earliest stages [12]. Therefore, this possibility suggests that emotion analysis, which is more sophisticated than sentiment analysis, is likely to become an important area of research in the future.

Emotion analysis research techniques are mainly divided into Emotion lexicon-based methods and machine learning-based methods. Firstly, emotion lexicon-based methods use an emotion lexicon to track the emotions in a text. An emotion lexicon is a human-made list of the emotions or sentiments evoked by words used in a text, mapped to predetermined emotional categories and positive or negative polarities. This is utilised to ascertain the emotional intensity of a text, predicted on the degree to which individual words are associated with a particular emotion [14]. The main emotion lexicons are *National Research Council Canada* (NRC) emotion lexicon and *Linguistic Inquiry and Word Count* (LIWC). The NRC emotion lexicon is the emotion lexicon developed by National Research Council Canada that utilizes English words mapped to eight fundamental emotions (Joy, Sadness, Trust, Disgust, Anticipation, Fear, Anger, and Surprise) and a positive or negative polarity [15]. The LIWC is a program that analyses text in order to quantify psychological and emotional situations. The LIWC was created by James Whiting Pennebaker who is a psychology professor at the University of Texas at Austin and it can be used to categorize words into different psychological categories using an extensive set of words [16]. The two approaches described have been employed to measure the proportion or intensity of emotions in a text. In particular, the simplicity and intuitiveness of the approach has led to its use in sentiment analysis in a variety of domains, including social media, literature and online journal texts [17][18][19]. However, emotion lexicons have a serious limitation, which is their lack of contextualization and inflexibility. This is because they are based on word-by-word analysis, which does not account for subtleties such as context and word polysemy. Consequently, it is not possible to analyse the multiple meaning of a word in different contexts. Moreover, like a real

dictionary, the fixed emotion quantitative score assigned to a word is unable to reflect the changing linguistic meaning over time [12].

Machine learning-based methods have emerged to compensate for the limitations of emotion lexicon-based approaches, particularly deep learning and transformer-based models, such as the BERT and ELECTRA models, which effectively leverage bidirectional contextual information to capture the different meaning and subtle emotional nuances that words can have in diverse contexts [10]. These models have been optimized for emotion analysis through purposeful pre-training and fine-tuning and have been shown to perform well in complex and fast-moving textual data domains such as social media, customer reviews, and audiences live chats [20][21][22]. This suggests that the field of emotion analysis is growing in both breadth of application and depth of analysis. Deep learning-based emotion analysis research is becoming more highly utilised than previous methods due to its increased accuracy and flexibility. However, it carries with it bias and cost. The process of hand-selecting training datasets for machine learning involves the possibility that the dataset is already not fair and biased. Furthermore, if the underlying training data is biased, the algorithm trained on it will learn this bias and reflect it in its predictions. As a result, these analysis will produce unintentionally biased results [23]. Additionally, there is the cost of acquiring high-performance hardware or GPU compute resources for training. This is a problem that did not arise with the emotion lexicon-based methods, and can be interpreted as a result of the fast growth of technology. Nevertheless, this relatively new method is already being applied to emotion analysis in various domains, and solutions to its weaknesses are being actively discussed [23][24]. Therefore, it is predicted that the potential for future improvement is as high as its young history.

The previously described emotion lexicon-based methods and machine learning methods are currently the leading approaches to emotion and sentiment analysis both. While there are certainly disadvantages to each approach, there are also attempts to compare and contrast the two in real research, as the most appropriate techniques may differ. For example, both techniques have been applied to analyse emotions in a literary text [25]. The works of Shakespeare were analysed using a deep learning model and

the *Valence Aware Dictionary and sEntiment Reasoner* (VADER) lexicon to compare which method captures sentiments more accurately [26]. In the experiment results, the overall sentiment analysis results of the text were similar for both techniques. However, analysis of individual works showed that deep learning models were more sophisticated and more accurate for literary works with more conflict and complexity [25].

In addition, since 2018, emotion analysis research is expanding its domain by applying innovative methods that have evolved from classical analysis [27]. One of the most popular applications is emotion recognition in conversation in various domains, which mainly involves analysing the emotions expressed during interactions. This approach can be used to analyse the flow of emotions in interpersonal interaction [27][28][29]. Furthermore, emotion analysis is being studied for mental health care purposes in the field of psychology or medicine [30], and is expanding to detect misinformation and evaluate moral content in the domains of communication and sociology [31][32]. In the field of economics and finance, it is also used to predict financial markets and economic trends using data from various domains [33][34]. Additionally, in the humanity domains, there are growing attempts to analyse emotions in literary texts [18][25][35][36][37]. As this study also conducts emotion analysis based on the literary text, the next part of this chapter will take a detailed review of which literary texts are used in the emotion analysis process and what specific purposes and research methods are used, and how they have been diversified.

2.2 Emotion Analysis in Literature

One of the earliest and most widely studied literary texts for emotion analysis is the plays of William Shakespeare [18][25][35][37][38]. Shakespeare's plays represent an important place in the history of English literature, and the fact that they are full-play scripts means that the dialogue between characters and dramatic conflicts are relatively clear, making them suitable for emotion analysis. For this reason, the XML files of the complete Shakespeare plays were made available as open source early on, making them accessible to computer-based literary research. Moreover, his representative works of

four tragedies (*Hamlet*, *King Lear*, *Othello*, *Macbeth*) and five comedies (*The merchant of Venice*, *The Taming of the Shrew*, *a midsummer night's dream*, *as you like it*, *twelfth night*) are convenient to grasp the basic polarity such as binary classification of emotions which are positive and negative in text sentiment analysis, as well as the flow of emotions in the play and social relationships between characters can be analysed more effectively [25][38]. The second category of texts to gain traction after Shakespeare is folk tales or fairy tales [18][36][39][40]. The relatively short length and clear structure of fairy tales lends itself to identifying and annotating emotions in texts comparatively simply. For example, as fairy tales are aimed at younger readers, they tend to be more straightforward to analyse in terms of emotions, with relatively flat plots rather than complex character relationships or dramatic plot twists. Moreover, Samuel Beckett's plays, *Not I* and *Come and Go*, which are experimental texts, have been studied for emotion analysis [41][42]. Beckett's literature is considered a challenging text, with a more sophisticated and non-linear narrative structure than the previously mentioned texts and is often used in computer-based literary studies for in-deep author-text analysis. In other cases, a study of emotion patterns has been conducted using a large number of stories from Project Gutenberg's large novel collection [43]. And literary texts from different eras and genres have been used extensively to analyse emotional trajectories in narratives [44]. The results demonstrate that literary texts across genres and time periods, including plays, fairy tales, and full-length novels, are being analysed for emotion studies.

A typical objective of emotion analysis in literary texts is to analyse the flow of emotions in a work and to interpret the narrative structure or literary meaning in a creative way. For instance, research has been conducted to predict the sentence-by-sentence emotions of literary texts and observe the emotional changes over the entire narrative section to clearly identify the emotional response of readers or the characteristics of the genre [18][36]. In the case of Shakespeare's plays, the structure and interaction of the play has been observed by analysing emotional dynamics and social networks between characters [35][38]. In Beckett's plays, the linguistic experiments of the author have been analysed in detail, focusing on literary features such as repetition [41][42]. Therefore, all of these studies covering various genres and

narratives have opened up a new range of possibilities for interpreting literary texts by tracing the emotional structures inside the works. The other important purpose is to measure reader response and influence. This is to quantitatively measure how a literary text affects readers and how well-received it is. In order to measure this, there has been research to correlate emotional structure with reader response by identifying the emotional flow of a story and actually examining whether certain patterns of stories result in higher sales [43]. Besides, some studies are attempting to provide sentiment-based search interfaces by using sentiment dictionaries to find sentiment-dense regions in large literary collections and linking them with visualisation tools [18]. This approach not only enables efficient navigation and analysis of the enormous number of literary texts on the Internet, but also has the potential to be applied in various fields beyond literary research, such as literary education and recommendation systems. Lastly, there is the purpose of methodological comparisons and in-depth literary studies. This means examining the methodology of emotion analysis itself or comparing it with other methods to analyse which method is more appropriate for analysing literature [25]. For example, there has been a lot of research on applying deep learning techniques and emotion lexicon methods to complex literary texts to monitor which one is more proficient. Furthermore, an attempt has been made to build multi-label emotion data to analyse situations where multiple emotions can exist simultaneously in a single sentence, and to apply semi-supervised learning to further elaborate complex sentiment structures [45]. Other studies are attempting to develop new interpretive approaches in combination with computer-aided literary studies [41][42], such as in-depth author-text analysis of linguistically challenging texts. To this point, the analysis of emotions in literary texts has developed around three main objectives, interpreting the emotional structure and narrative of a work, measuring reader response and impact, and comparing and studying analytical methodologies in depth. Each of these purposes is carried out independently, however, in actual research, they are often combined with each other to achieve a multi-layered analysis of literary texts. Therefore, based on the main objectives, it is interpreted that research is being developed to capture the emotional aspects of literary works in a richer way, and to examine the interaction between readers, writers, and narrative structures more broadly.

Methodologies that fulfil the three objectives described above can be broadly categorized into sentiment lexicons, machine learning, and hybrid approaches that combine the two. In the following, we summarize the historical development of emotion analysis in literary texts, focusing on a chronological overview and additional examples. In the early days of sentiment analysis of literary texts, in the mid 2000s, sentiment lexicons were used to intuitively classify words into positive, negative, or various sentiment categories. For example, word lists defined by NRC, *Affective Norms for English Words* (AFINN) [46], and so on were used to intuitively determine which sentiment category a matching word belongs to. This method is relatively simple to process, and therefore easily applied to early literary data such as fairy tales and short plays. Since the mid 2010s, there have been experiments with large-scale text quantification and visualization using emotion lexicon. For example, NRC emotion lexicon have been applied to literary collections of Grimm's fairy tales to quantify emotions in text and represent them in graphical visualizations [18]. There were also studies that applied AFINN lists to Shakespearean plays to visually analyze the emotions between characters and the social networks within the plays [35][38]. This period can be interpreted as a time when cases have been accumulated that demonstrate the intuitiveness of the sentiment lexicon-based approach to text interpretation. However, it was impossible to achieve a certain level of sophistication due to the limitations of context-driven interpretation, neologisms, and metaphorical expressions. As a result, machine learning techniques were experimented more widely, and hybrid approaches to overcome these limitations.

Machine learning-based methods can be largely categorized into pre-deep learning and post-deep learning. The pre-deep learning period starts with attempts at statistical methods in the mid 2000s. There was a study attempted to manually annotate 1,580 fairy tale sentences and track the flow of emotions in order to connect them to speech synthesis [40]. Also, text-based emotion prediction was attempted using deep learning *Sparse Network of Windows* (SnoW) structures [39][47]. Thus, this period anticipated the possibility of combining statistical techniques with machine learning. Later, efforts were made to create emotion labels that humans actually recognize and use them in machine learning by asking general readers to label sentences in a folk fairy tale text

without examples [36]. This is a strategy for using universal sentiment data in supervised learning and is indicative of the interest in machine learning-based emotion analysis. After 2010, machine learning approaches extend to complex algorithms and narrative analysis. A new study applied a variety of algorithms, including matrix factorization, supervised and unsupervised learning, to large-scale novel texts to identify six core emotional trajectories which are ‘Rags to riches’(rise), ‘Tragedy’ or ‘Riches to rags’(fall), ‘Man in a hole’(fall-rise), ‘Icarus’(rise-fall), ‘Cinderella’(rise-fall-rise), ‘Oedipus’(fall-rise-fall) [43]. This suggests that emotion analysis of literary texts can expand beyond simple emotion classification to include story structure and prediction of literary success. Besides, there have been attempts to quantitatively interpret emotions in literary texts by comparing and combining traditional corpus analysis with deep learning models. Some studies have aimed to quantify specific literary features such as repetition [41], or to analyze the comparison of the output of deep learning and dictionary-based techniques on Shakespearean plays [25]. In the 2020s, recent research has been centered on deep learning, with a variety of studies such as multi-label and BERT-based in-depth studies drawing attention. The development of artificial literary evaluation indicators [37], multi-label emotion analysis [45], and BERT-based author-text in-depth studies are representative [42]. Through these studies, emotion analysis of literary texts is getting deeper and further, and there is an attempt to interpret the author's linguistic structure and emotional expression in complex literary works by computer-based approaches [42].

While deep learning-centric techniques are becoming more mainstream in literary text emotion analysis, hybrid approaches are still being explored. This is because it can use the combination of the intuition of emotion lexicon and the contextual processing capacity of deep learning. This hybrid strategy can enhance the interpretability of complex literary texts while maintaining high accuracy and is being applied to a wide range of literary texts, including Shakespeare's plays [25][37][38]. It has the potential to be used not only for literary texts, but also for many other domains where emotion analysis is required, such as social media, news, customer reviews, and so on, as an alternative that compensates for the weaknesses of different approaches. To summarize, study methods for emotion analysis of literary texts are evolving into

lexicon-based, machine learning-based, and hybrid. In particular, as deep learning techniques evolve, emotion analysis is expected to illuminate literary texts in more diverse and sophisticated ways, opening up the possibility of advanced textual interpretation and leading to novel and valuable research directions at the intersection of digital humanities and artificial intelligence.

3 Samuel Beckett and His Works

In this chapter, we examine silence and pause as key motifs in Samuel Beckett's works and discuss the dramatic and textual features of his major work, *Waiting for Godot*. In doing so, we provide details on why *Waiting for Godot* was chosen as a case study and how the non-linguistic element of 'pause' can be addressed in deep learning-based emotion analysis.

3.1 Silence and Pause

In Samuel Beckett's plays, as well as in his novels, poetry, prose, and other genres, silence is a key technical device [48]. This silence has been interpreted not simply as the absence of language, but as a device to maximise the gap between language and presence, the emotions that cannot be expressed in words. This section will first examine the meaning of silence as stated or intended by Beckett himself, then examine the interpretations of silence offered by various critics and ultimately synthesise the meaning of silence as a form of pause.

Beckett left evidence of a thorough calculation of silence, both in his directorial notes and in the actual rehearsals of his plays, making it clear that silence is not an accidental gap. Nathalie Léger wrote the following about Beckett's notes

«He calculates the amount of silence on one side of his directing notebook. He calculates per day, per month, per year, and makes a table of numbers. If there are 724 minutes of silence, 86,000 seconds of silence, 365 pauses, and one equivalent of 230 million seconds of silence----- how many 23-second increments of silence do you need to get to a total of 24 hours of silence? »[49]

As the text suggests, Beckett recorded the length of silence and pauses in minutes and seconds, in order to calculate, with extreme precision, the effect of silence on the play. In this way, he demonstrated that the moment when words disappear on stage is not merely a decoration, but functions as an organising principle of the play. Furthermore, as Beckett himself said, “Silence pours into this play like water into a sinking ship” [11]. indicating that Beckett deliberately designed the entire stage to be engulfed in silence over time.

Also, in his 1965 short film ‘Film’, which he directed himself, Beckett deleted almost all dialogue, experimenting with the possibility of revealing the psychology and existence of characters without language [49]. As a result, for Beckett, silence was an active artistic choice that amplified dramatic meaning and made the audience more intensely aware of the limitations and absurdities of words. In other words, silence is not a deficiency or a void [7], but rather a device that works to paradoxically reveal what language fails to do [48].

There are many critical views of Beckett's use of silence, but they all have in common that it reveals areas that are not captured by language. Leslie Kane, for example, distinguishes between lowercase silences and capitalised Silences, arguing that while the former refers to brief pauses between characters, the latter indicates a state of absence or emptiness that accumulates and eventually exceeds the limits of language [7]. The implication of this is that the more moments of dialogue breaks, the more the audience and characters alike become suspicious of the capacity of language, and the more emphasis is placed on what is not said.

Thomas Gould also emphasises that silence pervades Beckett's work and allows the reader or audience to perceive dimensions beyond the limits of language, which reaffirms that silence is a leitmotif rather than a mere empty space [48]. Similarly,

Steven Connor points out that repetition and pause are particularly prominent in Beckett's plays, which creates the paradox that the absence of words makes the characters' feelings of anxiety, loneliness, and glimmers of hope more pronounced [50]. In the end, Beckett's silences can be interpreted as a strategy to deny or postpone linguistic explanation, inviting the audience to fill in the gaps themselves.

Furthermore, his style of directing suggests that every pause has meaning. When Beckett directed his plays, he tightly controlled his actors' every movement, the rhythm of their dialogue, and the length of their silences. In 1967, as soon as the actor who was to play Endgame at the Siler Theatre recited the first line, Beckett immediately interrupted the dialogue and said, 'Faster here, and a little more accent in this part, a little more rhythm. No, don't laugh so loudly, just close your mouth and pretend the laughter is coming out of your throat' [49]. He was meticulous in his direction, even down to counting the number of steps his actors would take on stage, giving instructions such as, "Twelve steps here, four steps there, just to be clear, only four steps" [49]. This reveals that his theatre is not merely emotional improvisation, but rather meticulously designed stages that take into account both linguistic structure and non-linguistic behaviour.

There are many different interpretations of silence in Beckett's work, however, when it is implemented textually, it is usually expressed in the form of a 'pause'. In Beckett's work, pauses have several interpretations. Firstly, it represents absence and presence. When dialogue is interrupted, nothing is said, and it seems as if nothing is happening, but in fact, the emotions or situations that the characters are feeling become more pronounced [50][51]. Simultaneously, the audience recognises why no one is speaking, but they also experience the negative emotions contained in the pause. Second, as a dramatic experiment, pause disrupts the conflict-resolution structure expected in traditional theatre, or artificially suspends time. One of the characteristics of what Esslin describes as absurd theatre is that characters wait for something or repeat futile language with little narrative progression, and Beckett dramatises this suspension with pauses [51]. Lastly, the effect of directly experiencing linguistic limitations and absurdities is maximised through pauses. In other words, rather than understanding

events through dialogue, the audience is more acutely aware of their meaninglessness through the pauses in which the events themselves do not occur.

As a result, Beckett uses silences and pauses to make the audience and reader aware of what is not being said, forcing them to reconsider the entire way language and meaning work. In this respect, the technique can be interpreted as relevant to the question of how important non-linguistic elements are in the expression of human emotions today.

3.2 **Waiting for Godot**

Beckett's most notable work about 'pause' is *Waiting for Godot* (1953) [52]. This work is distant from the traditional structure of a play, with its beginning, development, climax, and ending, and is non-narrative through its repetition, incompleteness, and absence [53]. In this section, we examine the organizational structure of *Waiting for Godot* and analyse how pause is specifically used in the text and then discuss why we chose this as a case study for 'pause' research of emotion analysis.

Waiting for Godot is a tragicomedy in two acts in which the two main characters, Vladimir and Estragon, wait every day for the mysterious figure of Godot [54]. However, Godot does not appear until the end of the play, and in the meantime, the two characters repeat meaningless small talk, philosophical reflections, and verbal play [52]. Martin Esslin refers to this as an archetype of absurdist theatre and interprets it as a structure in which the characters remain in a state of waiting, with no conflict resolution or development of events [51]. This play is interpreted as progressing in a way that feels like a clock slowing down and then stopping entirely as well [53]. In fact, there is barely any intrinsic narrative progression between the first and second acts, and the second act ends by repeating the first. This non-narrative form leaves the reader or audience with questions about who Godot is and when Godot will arrive, but the play ends with no clear answers. As a result, they experience a vague absence, a *Waiting for Godot's* presence, but nothing is confirmed.

In this work, pauses in dialogue are marked in visible text as (Pause) and are clearly perceived by the reader. For example, in dialogue, pauses are used as shown below.

VLADIMIR: He said Saturday (Pause) I think.

ESTRAGON: You think.

VLADIMIR: I must have made a note of it.

He fumbles in his pockets, bursting with miscellaneous rubbish.

ESTRAGON: (very insidious) But what Saturday? And is it Saturday? Is it not rather Sunday? (Pause) Or Monday? (Pause) Or Friday? [52]

In this scene, pauses neither intensify nor resolve the conflict, but rather make stop the story, interrupting the progression of events. From the audience's point of view, time and events are paused, and they become aware of the emptiness of the stage. From the reader's point of view, the actual flow of the story is interrupted by pauses in the dialogue. The role of these 'pauses' is also important in terms of emotional expression, as the characters in the play rarely show clear emotions such as anger, sadness, or joy. Rather, they persist in emotional states of opacity, confusion, and bewilderment [55]. In doing so, Beckett more distinctly illustrates the process by which humans endure life through a cycle of waiting, constantly asking questions to which there are no obvious answers, as a visual mark of pauses.

As shown, *Waiting for Godot* is a work with non-narrative and semi-narrative characteristics, and the repeated pauses in the dialogue play an important role in the development of emotions. We believe that these characteristics can present new challenges for deep learning-based emotion analysis. Traditional literary text emotion analysis research has mainly focused on analysing texts with clear emotional expressions such as positive and negative emotions, anger, joy, and sadness. However, in this play, the non-linguistic marker (Pause) has a strong influence on the flow of emotions, while neutral or ambiguous states are frequently present [11]. For example, characters rarely use explicit emotional vocabulary, and emotions are expressed through hesitation, repetition, and silence. This structure of emotions through non-linguistic elements poses an interesting challenge for deep learning-based emotion

analysis models. In other words, it is necessary to examine how models interpret emotions in texts that lack explicit emotional vocabulary. Furthermore, if the same emotional state is maintained or subtle changes occur before and after Pause, this is an area that has not been studied in existing emotion analysis. Therefore, this study aims to quantitatively analyse the context of the pause in *Waiting for Godot* to explore the significance of non-linguistic and empty space elements in literary text emotion analysis.

Although other Beckett works also employ pauses, *Waiting for Godot* was chosen specifically for its potential to explore complex emotional structures and multi-characters analysis. Other Beckett works, such as *Endgame* and *Krapp's Last Tape*, have an overall tragic atmosphere. However, since this study aims to analyse the realm of complex emotions that are not easily perceived by humans, works that are dominated by negative emotions were initially excluded. *Waiting for Godot*, on the other hand, is a tragicomedy with elements of tragedy and comedy [54], and it's worth experimenting with to see if a machine can capture these complex emotions. Also, in order for the subjects' use of pauses and emotions to be compared in this study, it was necessary to have at least two protagonists who use pauses with similar frequency. However, in the case of *Happy Days*, even though there are two characters, almost all of the dialogue is spoken by only one character, and *Not I* is monologue driven, making a multi-person comparative analysis practically impossible. As a result, *Waiting for Godot* was chosen as the most appropriate Beckett text in which to compare and analyze the genre's complexity and the two protagonists' use of pauses.

Eventually, Beckett's deliberate use of pauses in *Waiting for Godot* is a key device that dominates the mood and emotion of the text. It functions as a purpose-oriented technique that effectively reveals the anxiety, curiosity, and futility that lurks within the act of waiting, and how humans continue to do so without clear answers. Therefore, as a methodological endeavour, quantitative analysis using deep learning models will be valuable in shedding new insight into the effectiveness of pauses and its emotional of meanings.

4 Methodology

In this chapter, we describe the development and application of a deep learning-based emotion analysis model for analysing emotions in literary texts. It covers the entire methodology from data preprocessing for emotion analysis to model training, evaluation, and data visualisation. First, the data preprocessing required to perform emotion analysis is described. The GoEmotions dataset is used to train the model, including the process of cleaning and labelling the textual data. After that, the process of converting dialogues from *Waiting for Godot* into XML format for emotion analysis of literary texts is described. The course on training deep learning models for emotion analysis uses the ELECTRA model and explains the fine-tuning process and optimisation techniques for multi-emotion analysis. It also presents methods to evaluate the performance of emotion analysis models, and uses F1-score, which is important in multi-emotion analysis, to evaluate the balance between precision and recall of the model, and analyses the results of emotion prediction on real sentences from the literary text. Lastly, in order to effectively present the results of emotion analysis, it explains how to apply Plutchik's emotion wheel theory to reorganise emotion categories and colour-code emotions to visualise the data. In conclusion, this chapter details the technical elements required to perform emotion analysis on literary texts and presents the overall research methodology.

4.1 Data Preprocessing

Data preprocessing constitutes a fundamental step in any natural language processing task. This stage involves the refinement of data for the purpose of the analysis and its adjustment to ensure sufficient performance. In this study, preprocessing was approached specifically for the analysis of multi-emotions in literary texts, given that the methods should be applied differently for each purpose to achieve suitable performance [56]. The preprocessing step is essential for both training and literary text data, and the method was applied differently for each data set.

4.1.1 Training Data

In this study, we used the GoEmotions dataset for training emotion analysis model. The reason for choosing this dataset can be explained in two main ways. First, it fulfils the general requirements for emotion analysis research. Second, it has characteristics that make it particularly suitable for analysing Samuel Beckett's literary work. To begin with, the GoEmotions dataset has several strengths as training data for emotion analysis. For one, it has a large dataset size, which means that the accuracy of the model can be expected to be high. The dataset consists of a total of 58,000 Reddit comments, including 43,410 training data, 5,427 test data, and 5,426 validation data. To improve the performance of deep learning-based emotion analysis models, a sufficient amount of training data is required, and GoEmotions is a large-scale emotion dataset that matches this need [8]. Second, the GoEmotions dataset provides diversity in emotion labels. While previous emotion analysis studies have mainly used small-item emotion analysis using emotion dictionaries or binary positive/negative emotion classification, GoEmotions provides a total of 28 fine-grained emotion categories, allowing for more sophisticated emotion analysis. These fine-grained emotion labels are advantageous for analysing complex emotional patterns in literary texts. Especially interesting point is

that the GoEmotions dataset allows identifying the neutral state of a text. Neutral refers to the absence of emotion and is not included in the same category as the 28 emotion labels. This is due to the structural differences between sentences that do not clearly show emotion and those that do. In the process of building the dataset, raters were asked to select neutral if they were unsure whether an emotion was expressed in a particular sentence. In this way, sentences that could not be clearly categorised as emotional were treated as unemotional. As this result, Neutral is not analysed alongside the 28 labels expressing emotion, but rather functions as a label to classify sentences lacking emotion separately [8]. Therefore, see Table 1, neutral is added separately from the 28 emotion labels and is treated as an independent classification for the absence of emotion. And third, it has high compatibility with Transformer-based models. In this study, ELECTRA which is the transformer-based model was used to perform emotion analysis [9], and GoEmotions training data was resampled to be used with Transformer-based NLP models for optimal performance.

Sentiment	Emotions
Positive	Admiration, Amusement, Approval, Caring, Desire, Excitement, Gratitude, Joy, Love, Optimism, Pride, Relief
Negative	Anger, Annoyance, Disappointment, Disapproval, Disgust, Embarrassment, Fear, Grief, Nervousness, Remorse, Sadness
Ambiguous	Confusion, Curiosity, Realization, Surprise

Table 1. Emotions Categories of GoEmotions There are 28 emotions including ‘neutral’.

On the other hand, the GoEmotions dataset has features that make it particularly suitable for analysing Samuel Beckett's literary works for emotion analysis research. To begin with, the dataset is built on modern English texts, which is advantageous for analysing Beckett's plays. *Waiting for Godot* was written in the mid-20th century and does not have significant linguistic differences from modern English [52], which is

important because it minimises the linguistic asymmetries that can occur when dealing with texts with different modes of expression, such as Middle English. Furthermore, the way emotions are expressed in *Waiting for Godot* matches well with GoEmotions' emotion labelling scheme. Beckett's plays are often ambiguous in their expression of emotions and difficult to categorise intuitively. While simple emotion categories (e.g., joy, sadness, anger, etc.), which are often used in traditional emotion analysis studies, cannot fully reflect these characteristics, GoEmotions not only provides emotion labels that include complex emotional states (e.g., confusion, curiosity, surprise, etc.), but also allows for multiple-label emotion analysis [8]. This allows for more sophisticated analyses, even when emotions are overlapping or ambiguously expressed in Beckett's text. Finally, the GoEmotions dataset is well-suited to analyzing Beckett's plays because it is built on Reddit comments and was specifically designed to capture how emotions are expressed in real-world text. Reddit comments, which are written in a rather casual, conversational style on a variety of topics, contain characteristics that allow speakers to express emotions without a clear intention or to change emotions in context [8]. *Waiting for Godot* also tends to convey emotion through ambiguous dialogue and repetitive language rather than direct emotional expression [11]. Therefore, a model trained on these features can better analyse emotional patterns in Beckett's play. In conclusion, the GoEmotions dataset is not only an ideal dataset for large-scale emotion analysis studies, but also has characteristics optimised for emotion analysis of literary works such as Samuel Beckett's *Waiting for Godot*. Therefore, this study aims to explore how emotion analysis of literary texts can be extended using the GoEmotions dataset to quantitatively analyse the impact of the non-linguistic element 'pause' on emotion flow.

In order to conduct such a study, it is necessary to first refine the dataset into a form suitable for model training. Accordingly, a data preprocessing step was performed prior to the training process to ensure that the dataset was suitable for analysis. The preprocessing stage involved the identification and removal of elements that were not represented within the analysis data. Initially, emojis that were not represented by text were removed. For example, emoticons such as 🤩 (excitement) and 🍀 (optimism) were removed because they were classified as emotions in the

GoEmotions dataset but were not used in literary texts and therefore could not be used for emotion analysis of this study [8]. In addition, unnecessary symbols, ;,) and (, were removed, as the GoEmotions' dataset contains emoticons that use symbols such as ':)' and ':(. Consequently, all special characters except alphabet, number, space, exclamation mark and question mark were removed. Consecutive spaces that were not necessary were also removed at this stage.

Furthermore, an imbalance of training data between emotion labels was observed. With ELECTRA, it was found that the accuracy of classification was lower for some emotions when the number of training data was lower than others [57]. Therefore, the data was scaled to be similar in advance. For example, there were 14,219 training data for one emotion, while there were only 77 training data for another emotion, an absolute difference of 14,142. This represents a relative difference of 18,339%, which can lead to a significant imbalance in the distribution of data between emotion labels. To resolve this imbalance, a process of balancing the number of samples per specific label was performed to approximately 1500 samples. This process involved adding duplicates of sparse data for each label, and resampling a large amount of data at random to achieve the right number. This resampling process resulted in the largest training data size of 3,212 and the smallest data size of 1,547 between the emotion labels to balance the imbalance. The relative difference after adjustment was significantly reduced by 108%, reducing the bias towards certain emotions and improving the balance between emotion labels. When data imbalance is severe, a machine learning model may have high accuracy on emotions with more data, but low accuracy on emotions with less data [57]. This increases the likelihood of overfitting to emotion labels with sufficient data during the learning process and leads to poor prediction performance for emotion labels with insufficient data. Therefore, to solve this imbalance, data rescaling techniques were applied to minimise the variance in the data distribution across sentiment labels, which aimed to balance learning across emotion labels, reduce bias towards specific emotion labels, and improve overall emotion prediction performance.

Lastly, the GoEmotions dataset was encoded for the purpose of facilitating its integration into the machine learning model. This was necessary because the GoEmotions dataset contains multiple emotions in one sentence at the same time. According to the emotion extraction results of the sample text in the GoEmotions dataset, it can have more than one emotion for each sentence, therefore We encoded it to handle one-hot and multi-label by creating a multi-hot vector with a position of 1 corresponding to each emotion index using the MultiLabelBinarizer [58].

4.1.2 Literary Text to Data

The data of literary text for emotion analysis was extracted directly from the text in the paper book and created in XML format. Firstly, the data extraction process was conducted utilizing a paperback edition of *Waiting for Godot*, authored by Samuel Beckett and published in 1956 by Faber and Faber. The book was scanned and extracted into a computer-readable text format using Apple's Live Text feature. The entire process was executed manually, and any identified textual errors were rectified during the extraction procedure. The computer-readable text was then processed into XML format to create the text for data analysis from pages 9 to 94, the total two act of the play. The XML format was based on the format of Jon Bosak's Shakespeare play scripts¹, and the only difference in format was the use of page breaks. Due to the relatively concise nature of the play, which comprises a total of two acts, page tags were added from their original xml example in order to facilitate comprehension of the intricate flow. The page tag comprised a <SUBHEAD> page number <SUBHEAD> inside a <SCENE> tag, with the remaining tags based on Jon Bosak's XML tag format, see Figure.1.

¹ Shakespeare in XML (<https://www.ibiblio.org/xml/examples/shakespeare/>)

```

▼<SCENE>
  <SUBHEAD>90</SUBHEAD>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>I felt lonely.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>I was dreaming I was happy.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>That passed the time.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>I was dreaming that</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <STAGEDIR>(violently).</STAGEDIR>
    <LINE>Don't tell me!</LINE>
    <STAGEDIR>(Silence.)</STAGEDIR>
    <LINE>I wonder is he really blind.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>Blind? Who?</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>Pozzo.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>Blind?</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>He told us he was blind.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>Well what about it?</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>It seemed to me he saw us.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>You dreamt it.</LINE>
    <STAGEDIR>(Pause.)</STAGEDIR>
    <LINE>Let's go.</LINE>
    <LINE>We can't.</LINE>
    <LINE>Ah!</LINE>
    <STAGEDIR>(Pause.)</STAGEDIR>
    <LINE>Are you sure it wasn't him?</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>Who?</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>ESTRAGON</SPEAKER>
    <LINE>Godot.</LINE>
  </SPEECH>
  ▼<SPEECH>
    <SPEAKER>VLADIMIR</SPEAKER>
    <LINE>But who?</LINE>
  </SPEECH>

```

Figure 1. Xml file of 'Waiting for Godot'

4.2 Model Training

A well-curated training strategy is essential for leveraging deep learning-based NLP models in emotion analysis research. Even when using the same dataset, a purpose-driven training strategy is required, one that is based on the research objectives of the study in context. The model training process presented below has been specifically designed for multi-emotions analysis of literary texts. And the experimental environment for this study was run at Google Collab for GPU usage.

4.2.1 ELECTRA Model

The deep learning model utilised in this study is the ELECTRA model, which was released by Google in 2020. It is founded on the transformer architecture and exhibits a comparable structure to BERT. The main feature of ELECTRA is a new pre-training process called Replaced Token Detection. It is trained by inserting ‘replaced tokens’ into some of the input tokens using a small generator model, and the discriminator predicts whether each token is replaced or not. It was demonstrated better performance with less computational resources compared to the BERT model based on *Masked Language Modelling* (MLM) [9]. Moreover, the highest micro F1 performance was found for the ELECTRA-small model [57]. As a result, ELECTRA-small was selected as the deep learning model for this study, considering the limited resources of the study and its superior performance.

4.2.2 Fine-Tuning process

In this process, we first analysed the length of training data sentences according to statistics and decided on a maximum length of 128 before tokenizing them to a suitable

size for balanced data analysis of all datasets. The process was limited to an appropriate size, with the advantage that this stabilized memory usage and prevented information loss, thus improving learning efficiency and model performance. The importance of accurately determining the appropriate length during this process is paramount, as increasing the length excessively can lead to memory wastage, while decreasing it to an insufficient degree may result in data loss. The input data was then optimized through the utilization of the TensorFlow Keras frameworks, with the dataset being converted into a TF dataset. To enhance the efficiency of the model, pre-trained weights were utilised for the majority of the layers, with the output layer being the only exception. This layer was subjected to random initialization, allowing the model to learn.

In a further fine-tuning process, AdamW, the most widely used optimisation technique, was used for stable machine learning training, with the hyperparameters learning rate set to 5×10^{-5} and weight decay set to 0.01. These settings are not a mandatory requirement, but a stabilisation of the training process is ensured by their inclusion. AdamW is an algorithm that aims to improve the generalisation performance of a model by decoupling weight decay from the computation of the gradient of the loss function [59]. The ability of a model to perform well on analysis or validation data based on what it has learnt from training data is referred to as generalisation performance. Therefore, increasing generalization performance is an important factor in ensuring the accuracy and reliability of research results. The learning rate and weight decay were determined by referring to the transformer models BERT and ELECTRA studies [9][10]. In general, for transformer model pre-training, the learning rate values from 2×10^{-5} to 5×10^{-5} is used to achieve high efficiency and stable learning, and the weight decay is 0.01 in most studies, which is used to avoid overfitting in training and maximize model performance.

Furthermore, it was designed to enable multi-label emotion classification, taking into account the possibility that multiple emotion labels may be assigned to a single sentence in the analysis data. The Binary Cross-entropy loss function was used, and TensorFlow Keras was employed to integrate the loss function with a sigmoid activation function using its built-in features to facilitate the optimization process. This

process can be considered an effective method for the calculation of numerical values when a given sentence contains multiple emotion labels concurrently for the emotion analysis study [8].

Lastly, the experimental setup was determined. The batch size of 32 and 64 were first compared in the ELECTRA-small model, and higher micro F1 score were observed for batch size 64 [57]. Following an experiment with the number of epochs, ranging from 5 to 20, it was ascertained that an epoch counts of 10 yielded the maximum micro F1 score. Specifically, the micro F1 score was significantly lower at 5 epochs, indicating insufficient training, while increasing the epoch count to 20 led to a decline in performance, likely due to overfitting. Therefore, the training was performed with a batch size of 64 and an epoch of 10.

4.3 Evaluation

It can be difficult to evaluate the performance of a model using average accuracy or precision results since multi-label emotion analysis is characterised by label imbalance in the data and multiple sentiment labels can exist simultaneously. Therefore, we used f1-score, which is a harmonic mean of precision and recall, to evaluate the performance of such emotion analysis [8][60]. F1-score is essential for multi-label emotion analysis because it ensures that a small number of emotion labels in the data are not missed under label imbalance. When multiple emotions appear simultaneously in one sentence and multiple overlapping labels need to be predicted, the F1-score provides a balanced evaluation by considering both precision and recall. In emotion analysis, it is crucial to minimize false positives, which occur when an emotion that is not present is incorrectly predicted. At the same time, reducing false negatives is equally important to ensure that emotions actually present in the sentence are not overlooked. The f1-score is suitable for verifying the balance between the two metrics precision and recall, avoiding situation where either metric is extremely biased.

In the case of the GoEmotions dataset, the use of the BERT-base model yielded an average macro f1-score of 0.46, indicating the presence of scope for improvement. It can be anticipated that the adaption of new approaches will lead to an improvement in performance [8]. For the other emotion dataset, the average micro f1-score attained a maximum of 0.56 with the transformer model, with the ELECTRA-small model achieving the highest score [57]. Based on previous studies, a minimum average f1-score of 0.53 was planned for this study, resulting in a macro f1-score of 0.56 and a micro f1-score of 0.55.²

Prior to the comprehensive analysis of the entire literature text, experiments were conducted to predict the emotion of single sentences. This experiment employed models that had been trained, and the outcomes are presented in Table 2. Given that machine learning models, particularly the ELECTRA model with its bidirectional structure, are designed to reflect the context of the sentence, the results of the emotion analysis of the single sentence may not always align with those of the full text analysis [9]. However, in this evaluation, the initial focus was on assessing the efficacy of the training through a single sentence analysis.

The sentence used in the evaluation were selected from the analysed data, *Waiting for Godot*, and consisted of sentences with related words to examine the accuracy of distinguishing between positive word ‘good’ and negative word ‘bad’. In order to test the model’s recognition of the emotion when ‘not’ and ‘bad’ appear together, we included the sentence with two negative words. Last, the sentence ‘Simply wait.’ was selected to evaluate the model’s ability to detect neutral emotion, as it does not reveal a specific emotion. In this study, a default emotion threshold of 0.5 was set to extract emotions with a probability of 50% or higher. Afterwards, the second highest emotion was also identified to ensure that the multiple emotions analysis was accurate.

The results show that the trained model is capable of performing single-sentence level emotion analysis. For emotion categories above the threshold of 0.5, the model

² Macro F1-score 0.5629 and Micro F1-score 0.5545 ± 0.0047

correctly predicted both positive and negative emotions, and correctly analysed sentence where two negative words was interpreted as positive. It also showed an accuracy of over 90% for neutral emotion. Furthermore, even for emotions below the threshold, the second-highest emotion probability was still within the range that humans would have predicted given the nature of the single sentence, thus it considered valuable results.

Single Sentence	Emotions (%)
Oh very good, very very good.	Admiration 95.80% Approval 5.26%
That seems a good idea all right. But could we do it? Is he really a sleep?	Curiosity 65.50% Admiration 41.30%
He's not bad looking.	Approval 71.34% Admiration 20.39%
That would be too bad, really too bad.	Disapproval 74.23% Disappointment 16.93%
Simply wait.	Neutral 98.18% Annoyance 0.52%

Table 2. Emotion analysis results of Single sentences from *Waiting for Godot*

4.4 Data Visualisation

In this study, the emotion categories in GoEmotions were reclassified based on Pluchik's emotion wheel for visualisation purposes, and each emotion was given a colour to clarify the distinction. First, we reclassified the 28 emotions in GoEmotions by taking the two most contrasting representative emotions in the wheel, joy and

sadness, and reclassifying them as positive and negative sentiment respectively, with the rest of the emotions being classified as neutral. In this process, desire and embarrassment were moved to the neutral emotions, and neutral was also included as a neutral emotion label. Afterwards, yellow was assigned to positive emotions and blue to negative emotions, reflecting the colours assigned to joy and sadness respectively on the emotion wheel. Grey was applied to the neutral emotion category. This colouring highlights the contrast between emotions that are in complementary contrast to each other on the emotion wheel, and is useful for visualising differences in emotions more prominently with colour [61]. The reconstructed emotion categories and colour schemes based on the emotion wheel are shown in Table 3 below.

Sentiment	Emotions
Positive	Admiration, Amusement, Approval, Caring, Excitement, Gratitude, Joy, Love, Optimism, Pride, Relief
Negative	Anger, Annoyance, Disgust, Disapproval, Disappointment, Fear, Grief, Nervousness, Remorse, Sadness
Neutral	Confusion, Curiosity, Desire, Embarrassment, Neutral, Realization, Surprise

Table 3. Emotions Categories and Colors for Data Visualization

5 Results

In this study, we used deep learning-based emotion analysis to extract the emotions of the main characters in Samuel Beckett's *Waiting for Godot* and analyze the role of pauses in dialogues on emotional changes. In this chapter, we present the results of the emotion analysis of Estragon and Vladimir and a quantitative review of the role of pauses on emotions.

First, in Section 5.1, the main emotions were identified by analyzing the entire dialogues of the two main characters. The top two emotions per sentence were extracted and their frequencies were quantitatively measured to compare the distribution of emotions and differences in the way they were expressed. Next, in Section 5.2, emotions derived from sentences before and after pauses were analyzed, and the relationship between pauses and emotion changes was quantitatively examined. For this purpose, emotions of each sentence were extracted and then compared with the emotions before and after the pause to analyze the trend of emotion change. Finally, in Section 5.3, we grouped pre- and post-pause emotions to compare whether certain emotions are maintained or change after a pause. In particular, hypothesizing that the neutral emotion can serve as a point of reference for pre- and post-pause emotion changes, it analyzed the tendency of certain emotions to transition to neutral and the pattern of neutral states changing to other emotions after a pause.

This chapter presents the results of the analysis, focusing on the emotion analysis results and frequency data, while the role of pauses and the implications of emotional

changes on the interpretation of the works will be explored in depth in the Discussion Chapter.

5.1 Main Emotions

In this section, we analyzed the overall emotions of the main characters Estragon and Vladimir in *Waiting for Godot* based on their entire dialogues. Through quantitatively analyzing their dialogues, we examined how emotions were distributed in the dialogues and whether there were differences in the way they were expressed between the two characters.

5.1.1 Comparison of Emotion Distributions

After emotion analysis of Estragon's sentences in the entire text of the book, we found that there were 786 sentences spoken by Estragon, and the highest proportion of emotions was neutral with 682 (43.38%). In Table 4, curiosity had 261 (16.60%) sentences, followed by approval with 209 (13.30%) sentences. Also, based on figure 2, the frequency of emotions after that can be seen. Excluding neutral emotions, approval was the second highest, followed by negative emotions (disapproval 68, annoyance 49, sadness 27) and some neutral emotions (confusion 61, realization 28). Moreover, Figure 3, which divided the emotions into sentiment categories (positive, negative, and neutral) and expressed as a percentage, shows that neutral emotions accounted for the highest percentage (67.6%), followed by positive emotions (20.3%) and negative emotions (12.1%).

Emotion label	Percentage (%)	count
Neutral	43.38%	682
Curiosity	16.60%	261
Approval	13.30%	209
Disapproval	4.33%	68
Confusion	3.88%	61

Table 4. Estragon's Top 5 Emotions in the Full Text

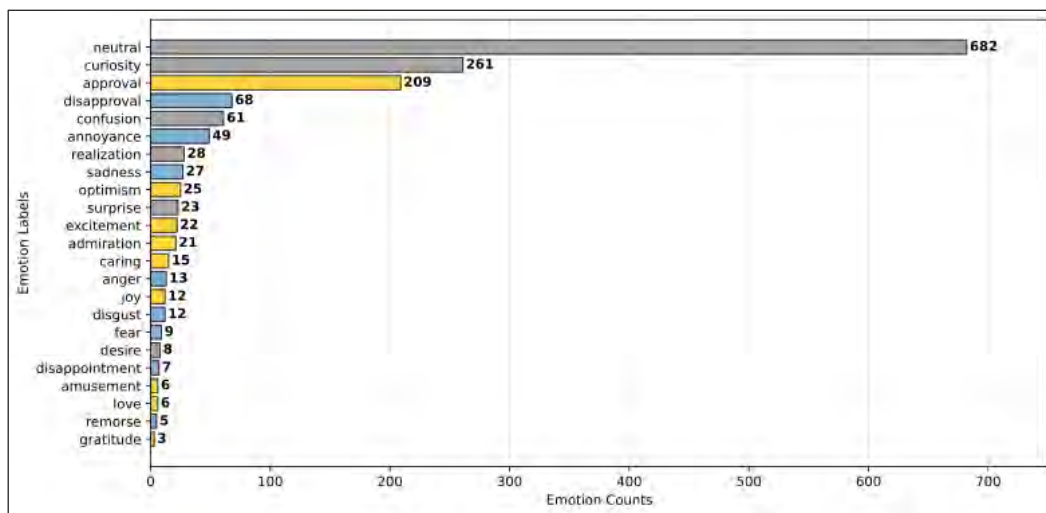


Figure 2. Frequency Distribution of Estragon's Emotions in the Full Text

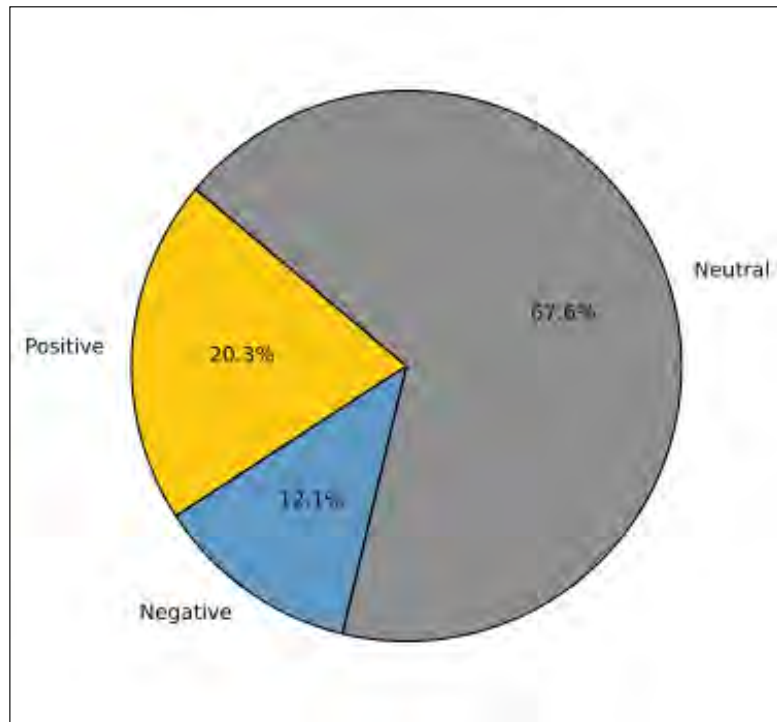


Figure 3. Percentage of Estragon's Emotions in the Full Text

On the other hand, In the case of Vladimir, the total number of sentences spoken in the entire text was 948, and as shown in Table 5, neutral accounted for the highest percentage of 42.72% (810). Next, approval was 15.40% (292), curiosity was 13.45% (255), and disapproval was 5.17% (98). Positive sentiment (approval) was the second highest overall emotion, but as figure 4 shows, the emotions after that were mostly negative (disapproval, annoyance, anger). In addition, Figure 5 shows that neutral sentiments were the highest percentage of the total emotion distribution (64.0%), followed by positive sentiments (23.0%), and the last negative sentiments (13.0%).

Emotion label	Percentage (%)	count
Neutral	42.72%	810
Approval	15.40%	292
Curiosity	13.45%	255
Disapproval	5.17%	98
Confusion	3.59%	68

Table 5. Vladimir's Top 5 Emotions in the Full Text

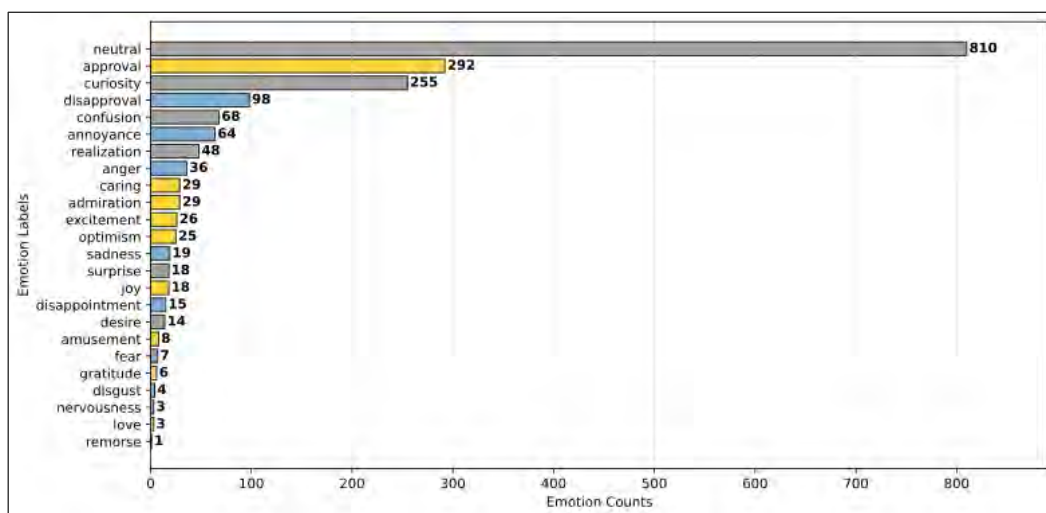


Figure 4. Frequency Distribution of Vladimir's Emotions in the Full Text

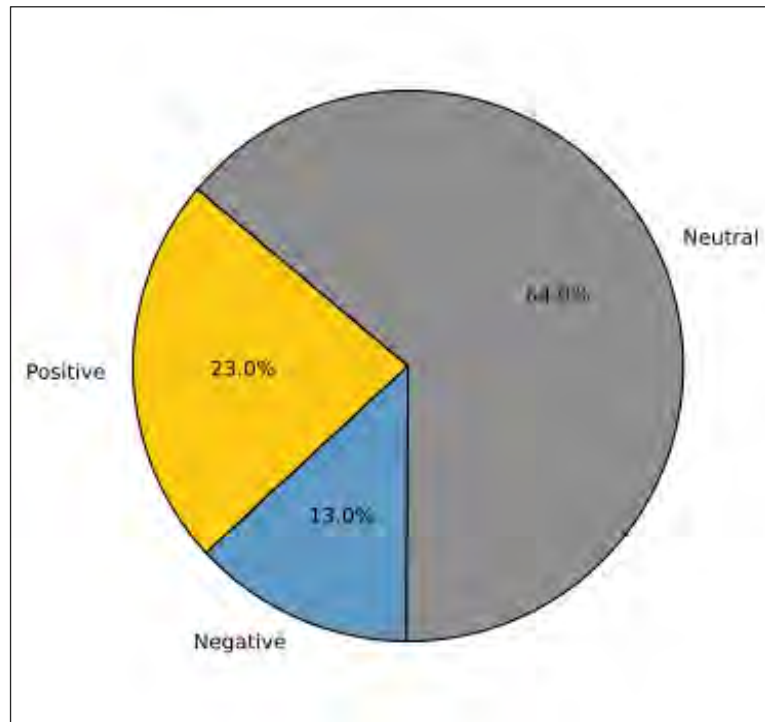


Figure 5. Percentage of Vladimir's Emotions in the Full Text

5.1.2 Differences in Emotional expression

For both main characters, Neutral was the highest percentage. With slight variations, Approval and Curiosity ranked after Neutral. However, there were differences in how they expressed their emotions. Estragon had a higher percentage of neutral emotions (67.6%) than Vladimir (64.0%), suggesting that Estragon tended to suppress his emotions or maintain an observer's attitude rather than expressing them directly. Vladimir, on the other hand, had a higher proportion of positive (23.0%) and negative (13.0%) emotions than Estragon, indicating a more direct expression of emotion. In particular, for negative emotions, Vladimir more often expressed emotions such as disapproval, annoyance, and anger, while Estragon's emotions included more neutral emotions such as confusion and realization. This suggested that Vladimir tended to

have a more explicit emotional response, whereas Estragon tended to be more introspective rather than immediately expressing his emotions. Therefore, the results of the emotion analysis showed that both characters are based on neutral emotions, but Vladimir expressed more direct and strong positive and negative emotions, while Estragon was more restrained in his expression.

5.2 The relationship between emotions and pause

In the previous section, we performed emotion analysis on the entire dialogue of the two main characters, and in the remaining two sections, we visually analysed the emotions associated with pauses. In order to explore the role of pauses more specifically, this chapter further analysed the emotions of the sentences surrounding pauses in a discrete manner. For this purpose, we first measured the frequency of pauses for two main protagonists, and then analysed the emotions of the sentences before and after the pause to extract the top two emotions per sentence. Afterwards, the extracted emotions were classified into before pause and after pause to compare and analyse the emotion.

For example, in Figure 1 below, the sentences around the pause can be analysed. In that speech tag, the sentence before the first pause is 'You dream it.' and the sentence after the pause is 'Let's go. In the same way, the sentence before the second pause is 'Let's go. We can't. Ah!' and the sentence after the pause is 'Are you sure it wasn't him?' All pauses were collected only within the character's speech tag, and words like pause outside the speech tag or silence inside the speech tag were excluded from the analysis. The actual emotion analysis results can be seen in Table 3.

```

▽<SPEECH>
<SPEAKER>ESTRAGON</SPEAKER>
<LINE>You dreamt it.</LINE>
<STAGEDIR>(Pause.)</STAGEDIR>
<LINE>Let's go.</LINE>
<LINE>We can't.</LINE>
<LINE>Ah!</LINE>
<STAGEDIR>(Pause.)</STAGEDIR>
<LINE>Are you sure it wasn't him?</LINE>
</SPEECH>

```

Figure 6. Example for emotion analysis of sentences related to pause

Page	Before Sentence	Before Emotion	After Sentence	After Emotion
90	You dreamt it.	neutral, annoyance	Let's go.	neutral, approval
90	Let's go. We can't. Ah!	disapproval, disappointment	Are you sure it wasn't him?	curiosity, neutral

Table 6. Example for the result of emotion analysis of sentences related to pause

Therefore, this section presents the results of analysing the emotions related to pauses in the dialogues of the characters in *Waiting for Godot*. For this purpose, firstly, the emotional distribution of the sentences before and after the pause was examined in general, and then the emotional difference between before and after the pause was analysed quantitatively. In addition, bar graphs and pie graphs were used to visually present the distribution of emotions related to the pause in each character's dialogue, and based on this, the similarities and differences between the two characters were presented.

5.2.1 Comparison of Pause-related Emotions

First, Estragon's pauses appeared a total of 19 times, and the emotion analysis of the sentences surrounding the pauses showed that neutral (30 times), curiosity (16 times), and approval (10 times) had the highest count of emotions, as shown in Table 4. The subsequent emotions are in the following order, as shown in figure 4, annoyance (5), confusion (3), disapproval (3), and disappointment (2), with the same predominance of neutral or negative emotions as in the full-text analysis. Furthermore, Figure 5, which visualises the emotions by sentiment category as a percentage, shows that overall, neutral had the highest percentage (65.8%), followed by an equal percentage of positive (17.1%) and negative (17.1%).

Emotion label	Pause Before Count	Pause After Count	Total Count
Neutral	14	16	30
Curiosity	6	10	16
Approval	4	6	10
Annoyance	3	2	5
Confusion	2	1	3

Table 6. Estragon's Top 5 Pause-related Emotions

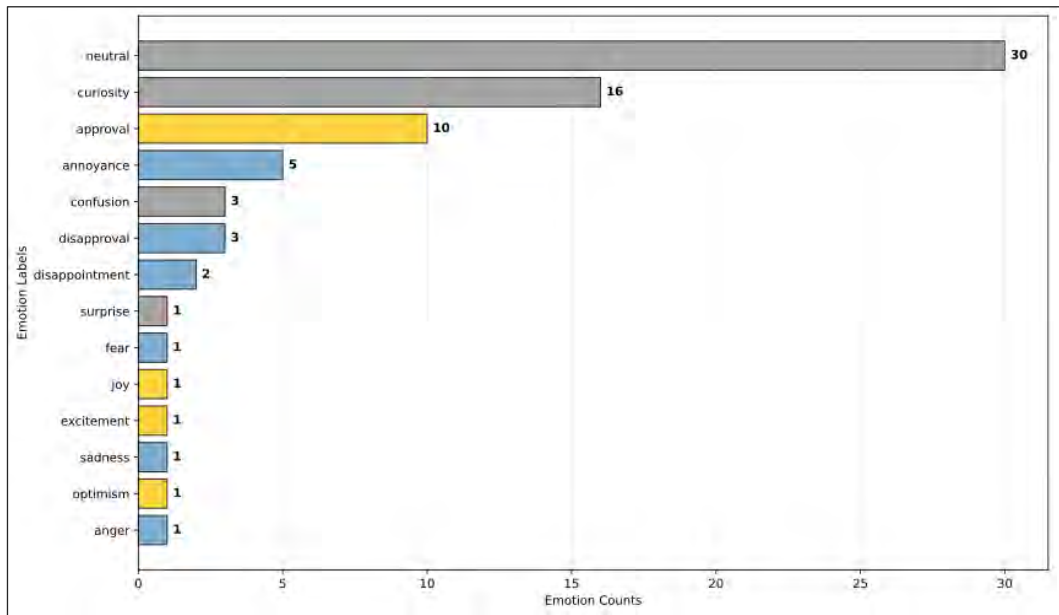


Figure 7. Frequency Distribution of Estragon' Pause-related Emotions

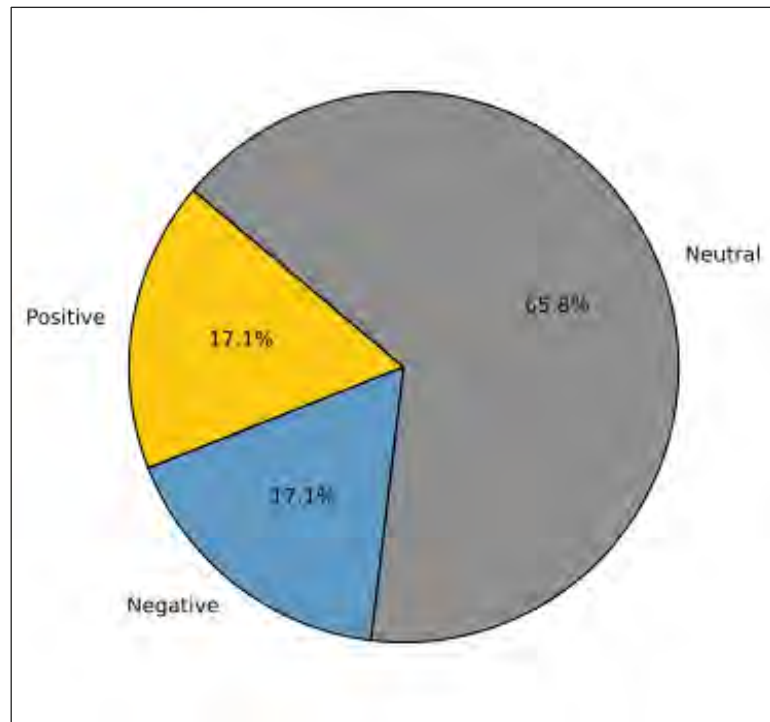


Figure 8. Percentage of Estragon's Pause-related Emotions

Meanwhile, Figure 9, the emotion analysis result of the sentence before pause, also showed that neutral (14), curiosity (6), and approval (4) were the top-ranked emotions, while the later emotions were mostly negative, including annoyance (3), disapproval (2), disappointment (2), fear (1), sadness (1), and anger (1). As a results, for the sentence before the pause, negative (26.3%) for the first time exceeded positive (13.2%) as a percentage of total emotions, as shown in Figure 7.

On the other hand, in Figure 11, the emotion analysis result of the sentence after the pause, the top emotions in the order of neutral (16), curiosity (10), and approval (6) were the same as the emotion analysis result of the sentence before the pause, but the overall percentage of negative emotions was low, and the positive emotion was 21.1%, which was more than twice as high as the negative emotion of 7.9%, as confirmed by Figure 12. In summary, negative emotions were higher in pre-pause sentences and positive emotions were higher in post-pause sentences.

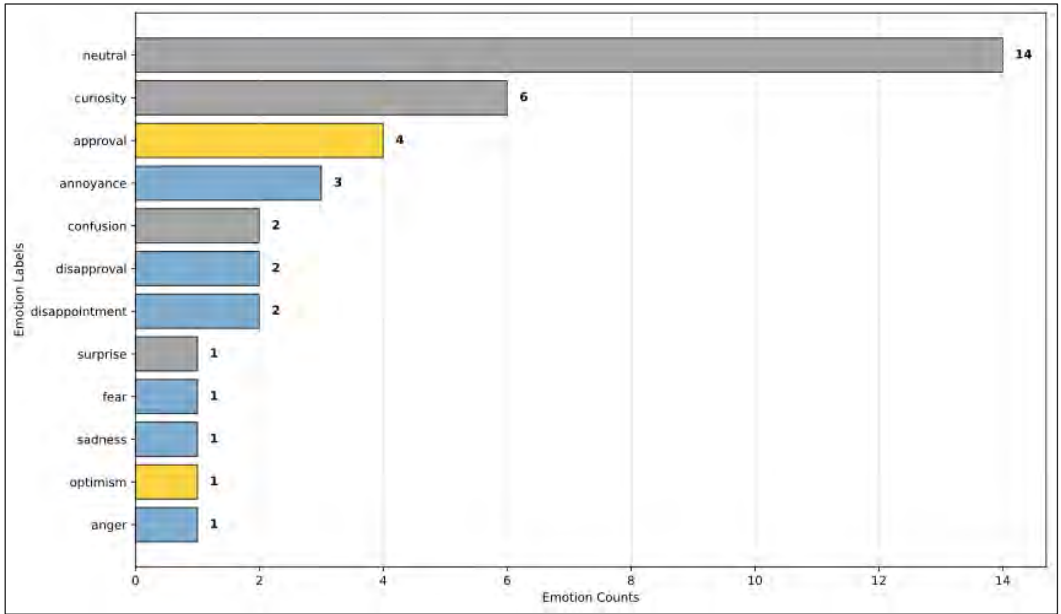


Figure 9. Frequency Distribution of Estragon's Pre-pause Emotions

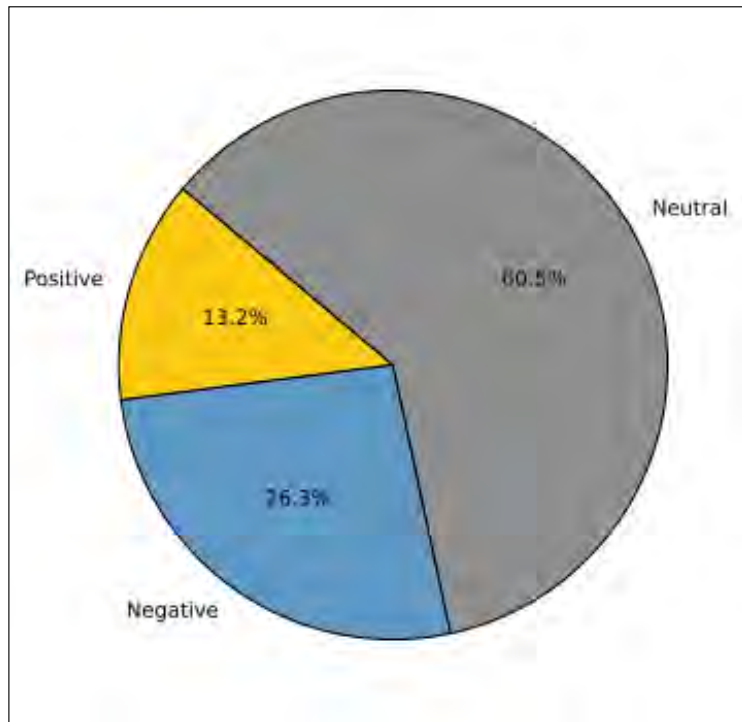


Figure 10. Percentage of Estragon's Pre-pause Emotions

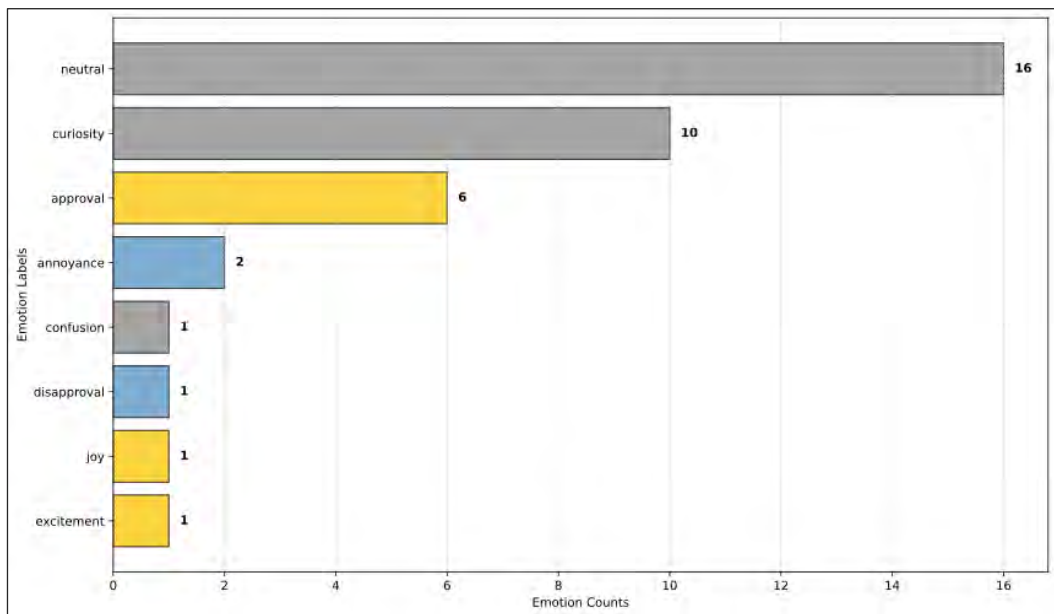


Figure 11. Frequency Distribution of Estragon's Post-pause Emotions

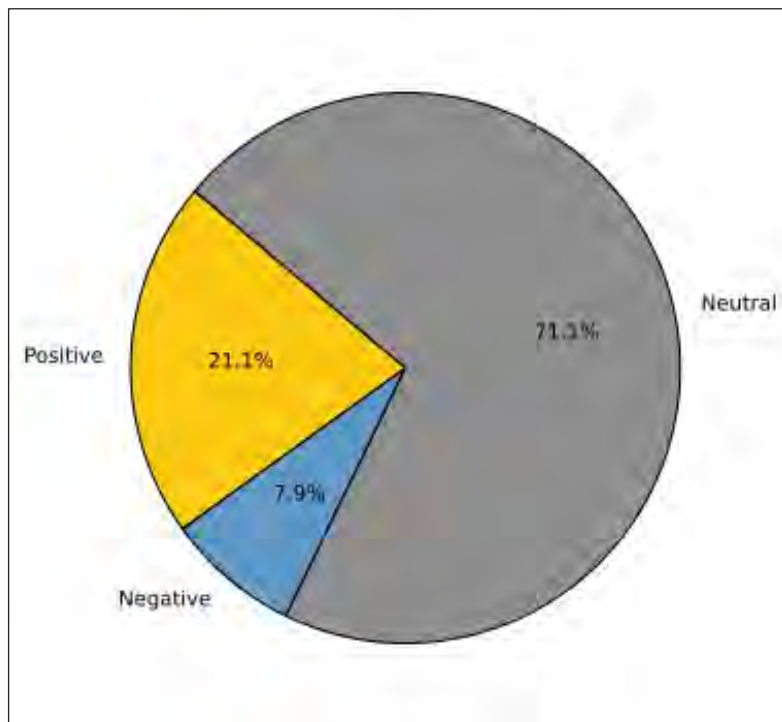


Figure 12. Percentage of Estragon's Post-pause Emotions

For Vladimir, the results of the visualisations in this section were broadly the same as those found previously based on the full text. In Table 7, Figure 13, Figure 15, and Figure 17, the frequencies of pause-related emotions, pre-pause emotions, and post-pause emotions showed the same trend, with neutral, curiosity, and approval at the top of all graphs. The pie graphs in Figure 14, Figure 16, and Figure 17 also showed a distribution of neutral, positive, and negative, consistent with the results based on the full text. However, there was one difference. In Figure 15, which represented pre-pause emotions, approval and curiosity tied for second place (12).

Emotion label	Pause Before Count	Pause After Count	Total Count
Neutral	30	34	64
Curiosity	12	15	27
Approval	12	12	24
Disapproval	4	3	7
Optimism	4	2	6

Table 7. Vladimir's Top 5 Pause-related Emotions

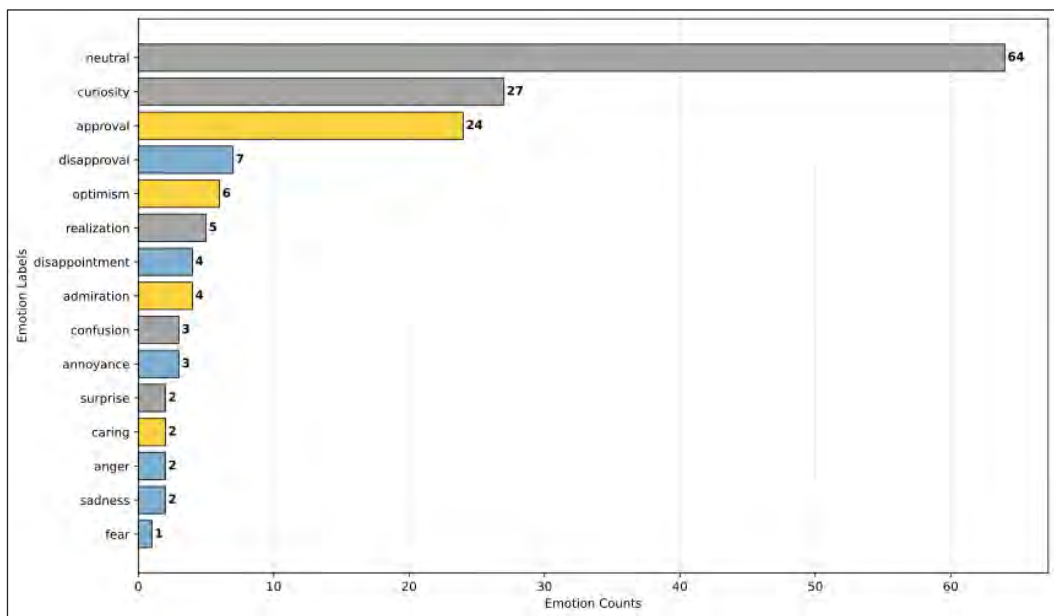


Figure 13. Frequency Distribution of Vladimir' Pause-related Emotions

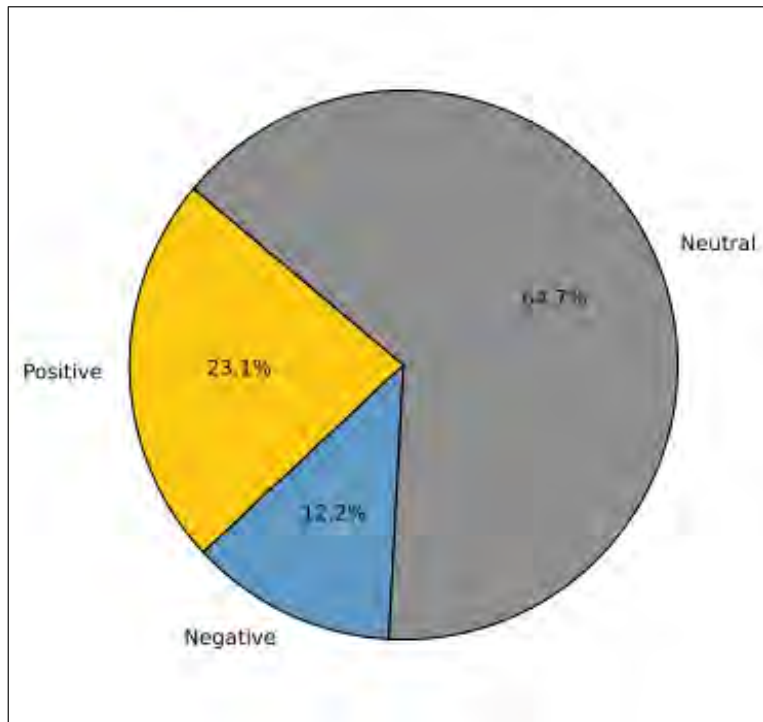


Figure 14. Percentage of Vladimir's Pause-related Emotions

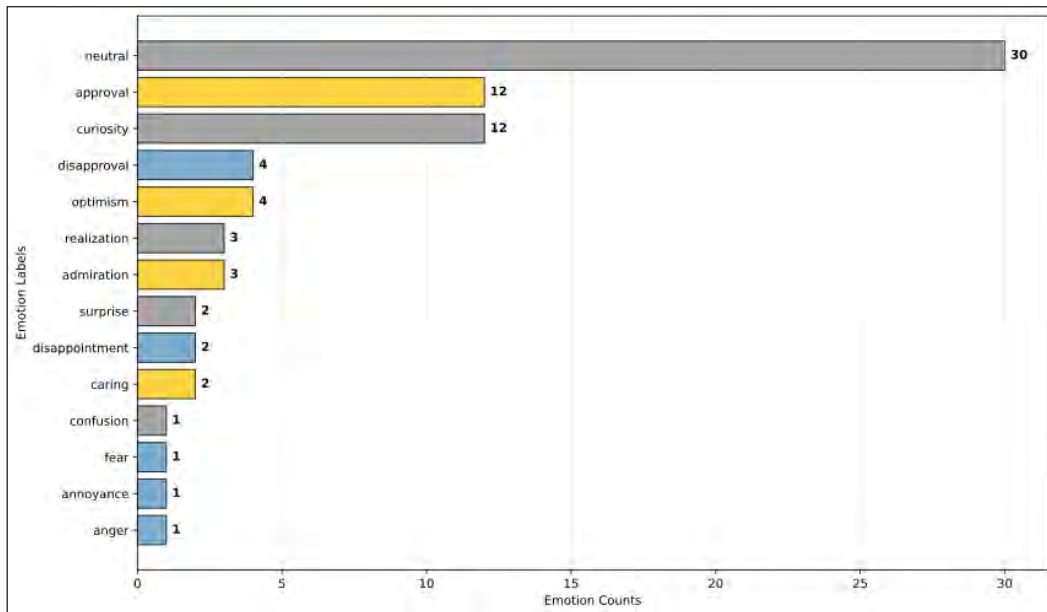


Figure 15. Frequency Distribution of Vladimir's Pre-Pause Emotions

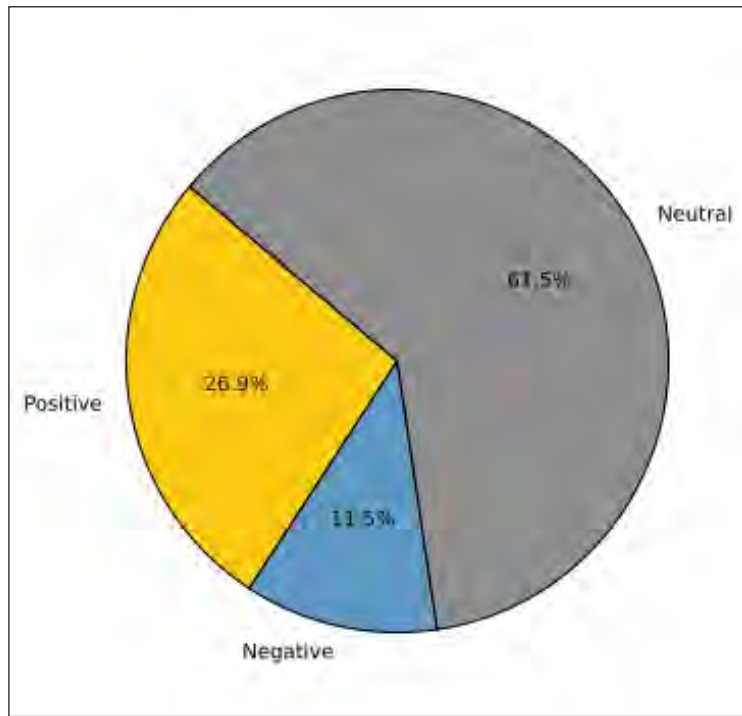


Figure 16. Percentage of Vladimir's Pre-Pause Emotions

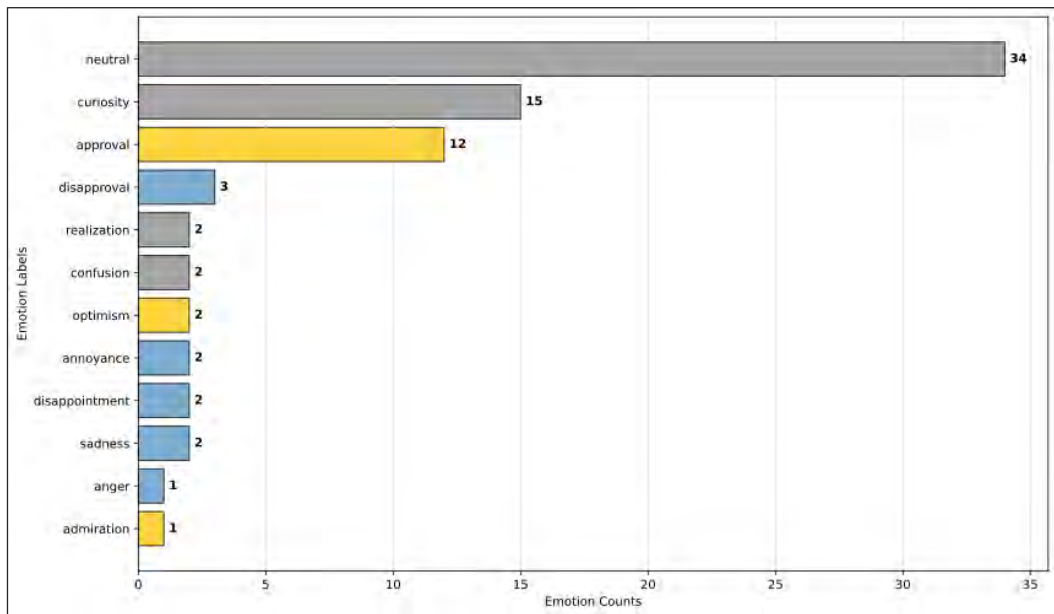


Figure 17. Frequency Distribution of Vladimir's Post-pause Emotions

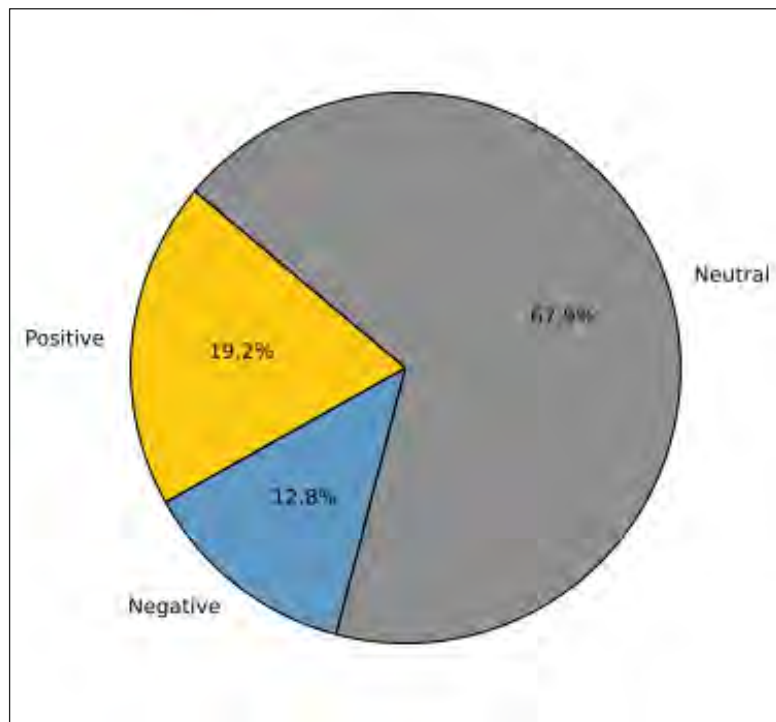


Figure 18. Percentage of Vladimir's Post-pause Emotions

5.2.2 Emotions differences between Before and After Pauses

After analysing Pause and its surrounding emotions for both characters, some similarities and differences were found. Firstly, neutral, curiosity, and approval were the top emotions for both characters, which was consistent with the emotion analysis of the entire text. In addition, both characters had the highest overall neutral emotional state. However, there was a clear difference between the two characters in the change in emotion before and after the pause. For Estragon, the proportion of negative emotions was higher than positive emotions in the pre-pause sentences, but in the post-pause sentences, the proportion of positive emotions more than doubled. This suggested that Estragon experienced a more dramatic change in emotion as a result of the pause. Vladimir, on the other hand, showed little variation in emotion before and

after the pause, and his sentiment ratio remained fairly consistent, with a slightly higher proportion of positive sentiment than negative. This suggested that Vladimir was more emotionally stable than Estragon, and that the pause had less of an impact on his emotional changes. As a result, Estragon's emotions fluctuated significantly with pauses, while Vladimir's emotions remained more consistent.

5.3 The role of pause

This chapter is the final result of the visualisation analysis and explored more specifically the role of pauses, which was the goal of this study. Based on the emotion data related to pauses collected in Section 5.2, the emotion changes before and after pauses were analysed in detail. In this visualisation, the pre-pause and post-pause emotion flows were analysed separately based on specific emotions. This allowed us to examine the impact of pauses on emotional changes.

In particular, we focused on neutral, which had the highest frequency across all analyses. Because neutral can be a reference point for emotional changes before and after pauses, we hypothesised that it plays a key role in assessing whether a pause maintains or changes emotions. Therefore, we analysed the tendency of certain emotions to change to neutral after a pause, and which emotions the neutral state mainly changes to after a pause. More specifically, we visualised the post-pause emotion of all results where the pre-pause emotion was neutral, and the pre-pause emotion of all results where the post-pause emotion was neutral. This was compared to the previous visualisation results to comprehensively analyse the relationship between pauses and emotions.

5.3.1 Patterns of Emotion Before and After Pauses

Firstly, for Estragon, as shown in Table 8, neutral accounted for 6 out of 10 in the top 5 pause-related emotion directions. When the pre-pause emotion was neutral, the

results of the post-pause emotion were shown in Figure 19, and this result was similar to the previous analysis, with the top emotions being neutral, curiosity, and approval. For the rest of the emotions, the sum of negative and positive emotions was equal in frequency (2). As a result, Figure 20 showed that neutral emotions tended to remain neutral after the pause, or change to mainly positive emotions.

Pause Before Emotion	Pause After Emotion	Total Count
Neutral	Neutral	12
Neutral	Curiosity	8
Curiosity	Neutral	6
Neutral	Approval	4
Approval	Neutral	3

Table 8. Estragon’s Top5 Emotion Direction Count (Emotion → Emotion)

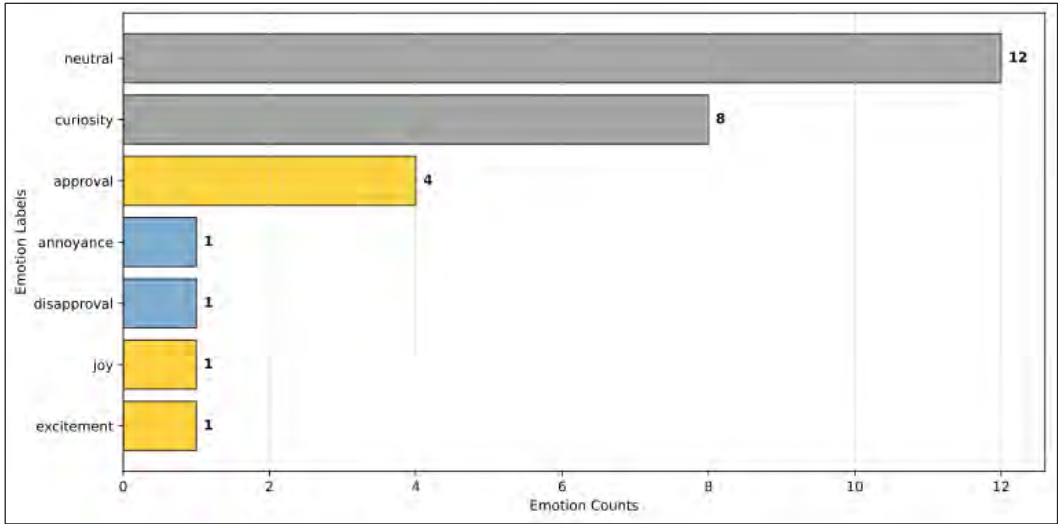


Figure 19. Frequency Distribution of Estragon’s Pause-Related Emotions After Neutral Emotions (Neutral → ‘Emotion’)

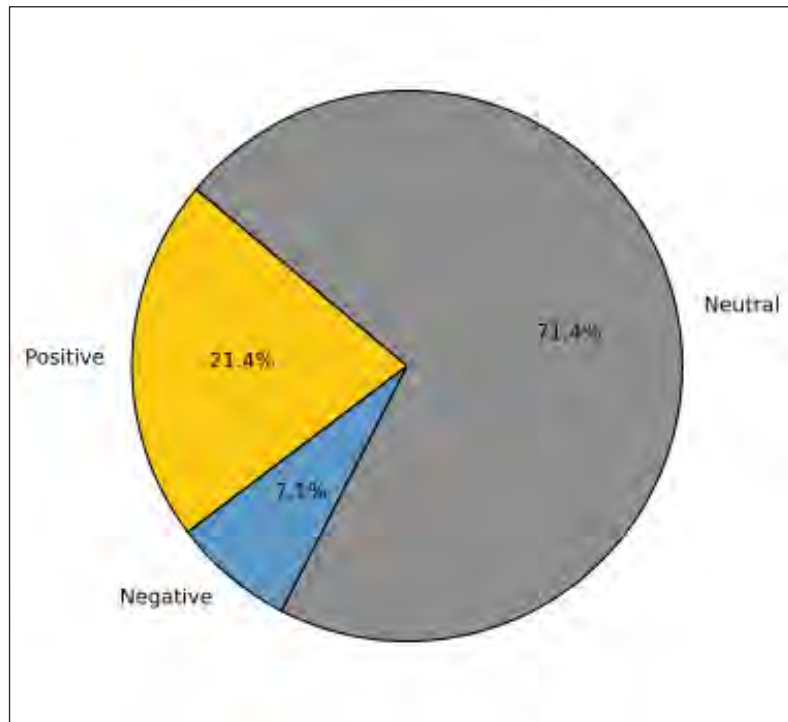


Figure 20. Percentage of Estragon's Pause-Related Emotions After Neutral Emotions
(Neutral → 'Emotion')

On the other hand, when the post-pause emotion was neutral, the distribution of pre-pause emotions tended to be different. According to Figure 21, it included various negative emotions such as annoyance (2), fear (1), sadness (1), anger (1), disapproval (1), and disappointment (1). And this result accounted for 21.9% of the total, the second highest percentage after neutral. Therefore, in the case of Estragon, Figure 22 showed that pause usually acted as a transition to neutral after negative emotions.

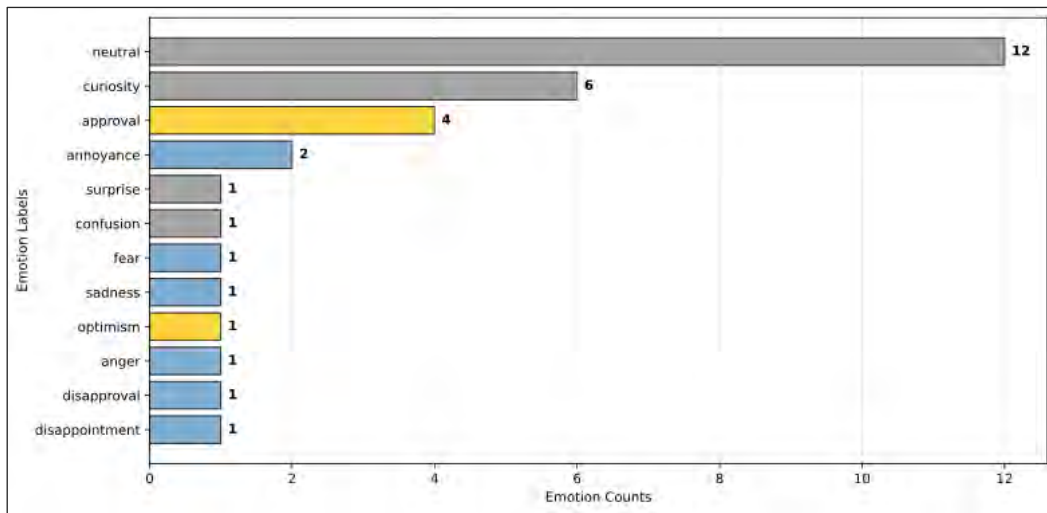


Figure 21. Frequency Distribution of Estragon's Pause-Related Emotions Before Neutral Emotions ('Emotion' → Neutral)

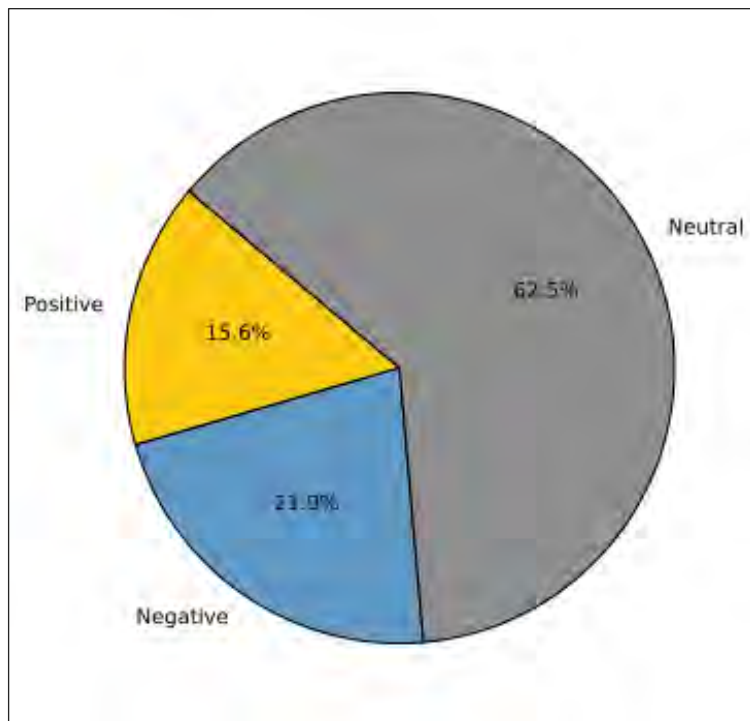


Figure 22. Percentage of Estragon's Pause-Related Emotions Before Neutral Emotions ('Emotion' → Neutral)

In the case of Vladimir, as shown in Table 9, neutral accounted for six of the top ten pause-related emotions. The results of the post-pause emotion, when the pre-pause emotion is neutral, are shown in Figure 23, where the top emotions were similar to the previous analysis. The remaining emotions were dominated by negative emotions (7), but as Figure 24 showed, the high frequency of approval emotion made positive sentiments the second highest percentage of the total emotions after neutral.

On the other hand, when the post-pause emotion was neutral, the distribution of pre-pause emotions tended to be somewhat different from the all previous results. As shown in Figure 25, overall, positive emotions were distributed at the top, followed by approval (11), optimism (4), admiration (3), and caring (2). As a result, positive emotions accounted for 29.4% of all emotions, which can be seen in Figure 26. This was a pie graph where positive sentiment was the highest percentage of the total sentiment, excluding neutral sentiment.

Pause Before Emotion	Pause After Emotion	Total Count
Neutral	Neutral	25
Approval	Neutral	11
Neutral	Curiosity	11
Neutral	Approval	10
Curiosity	Neutral	10

Table 9. Vladimir's s Top 5 Emotion Direction Count (Emotion → Emotion)

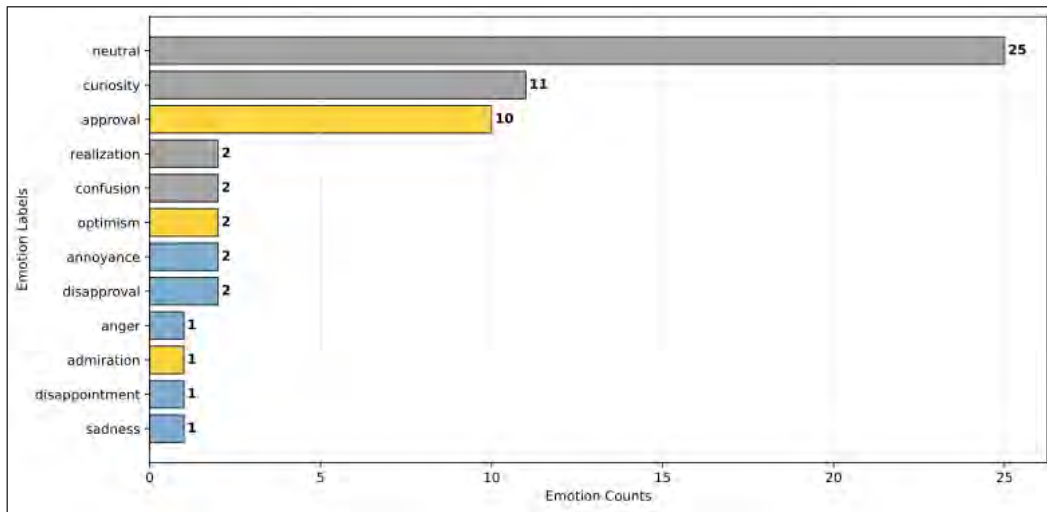


Figure 23. Frequency Distribution of Vladimir's Pause-Related Emotions After Neutral Emotions (Neutral → 'Emotion')

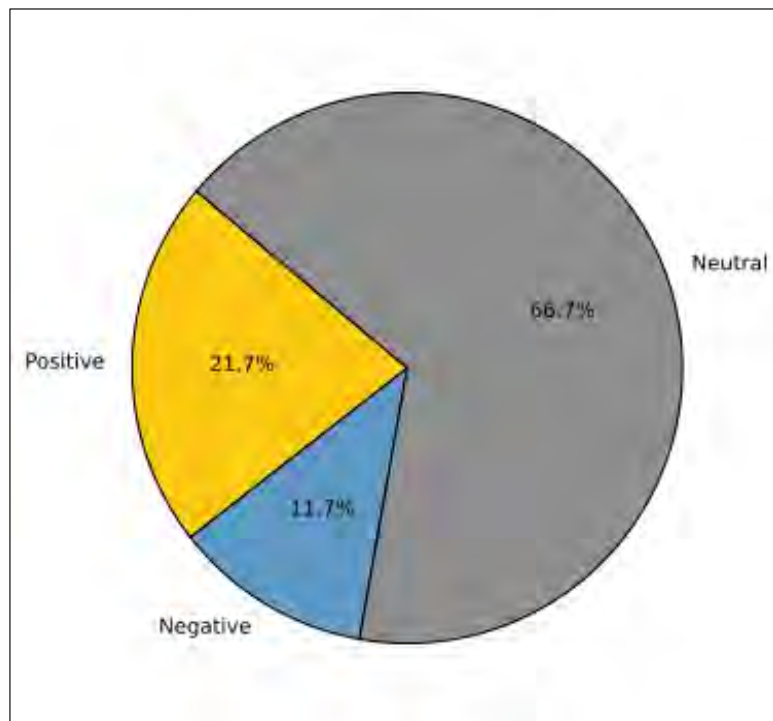


Figure 24. Percentage of Vladimir's Pause-Related Emotions After Neutral Emotions (Neutral → 'Emotion')

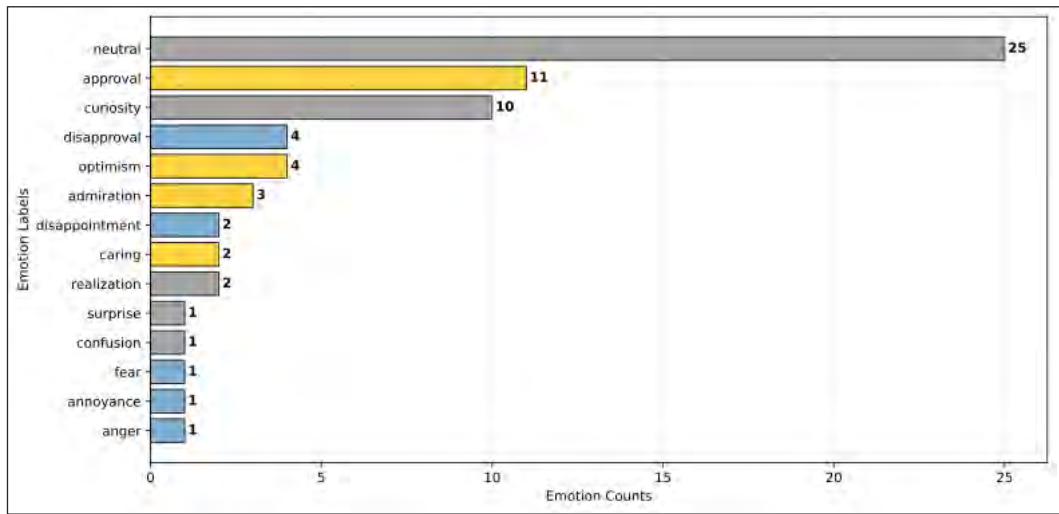


Figure 25. Frequency Distribution of Vladimir's Pause-Related Emotions Before Neutral Emotions ('Emotion' → Neutral)

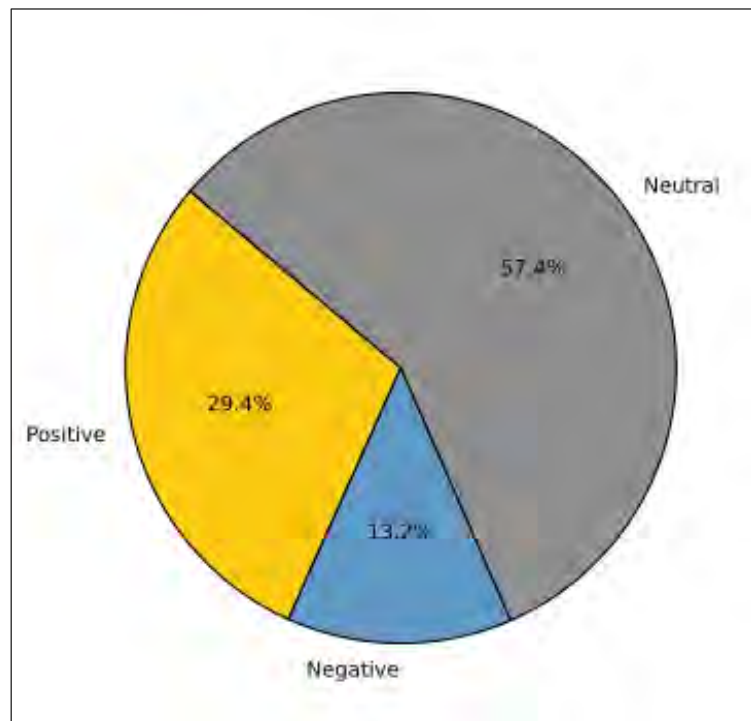


Figure 26. Percentage of Vladimir's Pause-Related Emotions Before Neutral Emotion ('Emotion' → Neutral)

5.3.2 Neutral Emotions and Differences between Characters

In terms of similarities and differences, the results showed that the neutral emotion plays a central role for both characters. This is because both characters had the highest frequency of neutral in their pre-pause and post-pause emotions. However, in the pie graph representing the overall percentages, there was a point where the percentage of neutrals was a bit different from the previous results. When comparing emotions before and after the pause, Vladimir had a relatively low percentage of neutrals overall. Comparing the percentages for the two characters, Estragon's Figure 20 and Figure 21 had 71.4% and 62.5% of neutrals, respectively, while Vladimir's Figure 24 and Figure 25 had 66.7% and 57.4%. Although Vladimir had a lower overall percentage of neutrals compared to Estragon in the previous pie charts, Figure 25 was the only one with a neutral percentage in the 50% range. In particular, in the previous pie graphs, Vladimir tended to have a lower percentage of neutral emotions than Estragon, but in Figure 25, he was the only case where the percentage of neutral emotions fell below 50%. This suggested that Vladimir had a lower percentage of pauses followed by a shift to neutral emotion, and that pauses may have a different effect on emotion change. In conclusion, both characters showed a change in emotion through pausing, but Estragon showed a stronger tendency to shift from negative to neutral. while Vladimir showed a higher percentage of positive emotions after pausing and also showed high percentage of neutral emotions after positive emotions.

In this study, deep learning-based emotion analysis was used to quantitatively analyze the emotional distribution of Estragon and Vladimir, the main characters of *Waiting for Godot*, and examined the impact of pauses in the work on emotional changes. First, in Section 5.1, we analyzed the emotions of the entire dialogue to see how and how much emotion was expressed by both characters. The analysis showed that both characters mainly expressed neutral, curiosity, and approval emotions. However, Estragon tended to express curiosity relatively more, while Vladimir expressed approval more often. Next, in Section 5.2, we analyzed the emotions of the sentences before and after the pause to quantitatively measure which emotions are dominant in

the context of the pause. The results indicated that neutral was the most frequently expressed emotion around pauses, followed by curiosity and approval. For Estragon, the percentage of negative sentiment was higher in the sentence before pauses, and the percentage of positive sentiment tended to increase after pauses. Vladimir, on the other hand, had relatively little change in sentiment before and after the pause, and his sentiment ratio remained constant throughout, in the order of neutral, positive, and negative. Lastly, in Section 5.3, patterns of emotional transitions were identified by analyzing whether certain emotions were maintained or changed after or before a pause. In particular, transitions from neutral to curiosity and from neutral to approval were common for both characters. In addition, for Vladimir, the overall percentage of neutrals tended to be lower than for Estragon when compared to the previous visualizations. In Figure 20 and Figure 21 for Estragon, the percentage of neutrals was 71.4% and 62.5%, respectively, while in Figure 24 and Figure 25 for Vladimir, the percentage was 66.7% and 57.4%, respectively. Especially, Vladimir had a lower percentage of neutrals than Estragon in the previous visualizations, but Figure 25 was the only result where the percentage of neutrals was in the 50% range.

In the following discussion chapter, based on the results of this study, we will compare how deep learning-based emotion analysis differs from traditional critical interpretations, analyse the functional significance of pauses in emotion structure, and discuss their impact on emotion flow.

6 Discussion

This study used deep learning-based emotion analysis to quantitatively analyse the emotional patterns and the role of pauses in *Waiting for Godot*. In this chapter, we discuss the academic contributions of this study through an in-depth interpretation of the relationship between emotions and pauses based on the results of the study and a comparison with previous studies. Additionally, we explore the extension possibilities of this study by exploring the impact of emotion analysis methods and artificial intelligence technology on the interpretation of literary texts.

In the literature, *Waiting for Godot* has been characterized as a departure from traditional dramatic structure, featuring stasis and repetition rather than narrative progression, which serves to emphasize the anxiety, loneliness, and helplessness experienced by the characters. In particular, Esslin cites the play as a classic example of absurdist theater, analyzing that the overall mood of the play is one of both hope and despair, with the characters constantly in a state of waiting for an uncertain future [51]. Many studies have also emphasized that Beckett's work uses long periods of silence and pauses to reveal the limits of language's ability to fully convey emotion. The results of this study's deep learning-based emotion analysis revealed both similarities and differences with these existing interpretations. First, in Section 5.1, the emotion analysis of the entire dialog showed that both characters mainly express neutral, curiosity, and approval emotions. This is consistent with previous studies that have analyzed Beckett's characters as remaining ambiguous or neutral rather than expressing their emotions clearly. Furthermore, these key emotions appeared in

proportions similar to those of the play as a whole and to the emotions associated with pauses, and were effectively analysed as a reflection of the author's intended mood for the play. The machine also did a relatively efficient analysis of the tragicomedy genre. Most of the pie charts stayed around 60% neutral sentiment, with the remainder showing similar proportions of positive and negative sentiment. This suggests that the machine understood that the play does not lean heavily towards any particular emotion, and that the tragicomedy genre has a balanced mix of tragedy and comedy. However, there were also differences. In particular, emotions such as fear and nervousness, which were highlighted in previous studies [50], were not included in the top emotions, and the overall emotional ratio of the play was not dominated by negative emotions. This difference suggests that the emotion analysis model was not able to analyse the main emotions of the play, which were analysed by traditional literary critics, and rated it as neutral. These results clearly demonstrate the uncertainty of Beckett's work, as most emotions are neutral or curious. However, the relatively low frequency of emotions such as fear, and nervousness also reveals a limitation. This can be interpreted as a result of emotion analysis models still being unable to accurately interpret the intent behind nuanced sentences and correctly analyse word meanings within context.

Previous research on pauses interpreted them as having a strong influence on the flow of emotion [11]. In this study, we analysed the patterns of emotional changes before and after pauses to quantitatively verify this interpretation. The results of the analysis revealed that pauses play an important role in modulating the flow of emotions, rather than simply changing emotions. In Section 5.3, we analyzed the patterns of emotional transitions and found that transitions and self-looping patterns in the three emotions of neutral, curiosity, and approval were frequent in both characters. This suggests that pauses tend to induce transitions within a particular emotion category rather than radical shifts in emotion, emphasizing that pauses do not suppress emotions or shift to new emotions, but rather increase the persistence of certain emotions. Furthermore, it was found that pauses are a key device for balancing emotions, which helps maintain *Waiting for Godot's* tragicomedy qualities. Tragicomedy is a genre that blends comedy and tragedy, and is characterized by the ambiguity of

emotions, rather than being one-sided. The emotion analysis demonstrated that pauses do not induce extreme emotional changes, but rather tend to gradually modulate emotions and maintain a neutral state. As the visualisation shows, Estragon's negative sentiment percentage (26.3%) in Figure 10 shifts to neutral after a pause, as shown in Figure 22. Similarly, Vladimir's positive sentiment percentage in Figures 16 and 18 shifts to neutral after a pause, as shown in Figure 26. This can be interpreted as a quantitative result of the analysis that for every element in the play that suggests bewilderment, meaninglessness, and anxiety, there is a line of dialogue, gesture, or emotional expression that subtly, and sometimes humorously, contradicts it, as in Graver's interpretation[11]. As a result, this suggests that rather than causing an immediate change in emotion, the pause acts as an adjustment to the natural cycle of emotions. Therefore, it can be interpreted that Beckett utilized pauses to orchestrate the flow of emotions and maintain the specific atmosphere of *Waiting for Godot*, rather than simply adding non-linguistic elements. These results indicate that the pause acts to maintain the overall emotional balance of the play rather than causing a drastic change in emotion.

In conclusion, the deep learning-based emotion analysis in this study shows similar results to existing literary studies, but also reveals some differences. First, the emotion analysis of Vladimir and Estragon showed that the two characters primarily express neutral, curious, and approval, which is consistent with existing research that Beckett's characters remain ambiguous or neutral rather than clearly expressing their emotions [51]. These emotions also occurred in similar proportions throughout the play and in the emotions associated with the pauses. Furthermore, the emotion analysis model recognised the emotional balance of the tragicomedy genre to a certain extent, with the results suggesting that the plays are composed of a mixture of tragedy and comedy without being biased towards any one specific sentiment. However, differences with previous studies were also found, particularly that emotions such as fear and nervousness, which have been highlighted in previous studies, did not appear as the dominant emotions. This suggests that the emotion analysis model does not accurately capture the emotions highlighted in the literature and tends to rate most of them as neutral. Regarding the role of pauses, previous studies have interpreted pauses

as regulating the flow of emotions [11], and the results of this study quantitatively supported this interpretation. In this study, pauses were found to play a role in sustaining key emotions in the play and maintaining emotional balance between tragedy and comedy. This study demonstrates the potential of deep learning-based emotion analysis to contribute to the interpretation of literary works, and provides a new approach to quantitatively analyse the impact of non-linguistic elements such as pauses on emotional expression. This research will expand the intersection of sentiment analysis and literary studies, while opening the way for future explorations of the role of the non-linguistic in a variety of domains.

7 Conclusions

The aim of this study was to identify the role of pauses in the literary text *Waiting for Godot* by Samuel Beckett through deep learning-based emotion analysis. Based on the results of the study, first, the relationship between emotions and pauses and the role of pauses will be interpreted, followed by a comparison with previous studies to discuss the academic contributions and suggest possibilities for future research.

7.1 Study summary and key contributions

This study analysed the role of pauses quantitatively through deep learning-based emotion analysis and compared it with previous studies in the literature. Previous studies have interpreted pauses as a factor that regulates the flow of emotions [11], and the results of this study quantitatively supported this. The analysis showed that pauses play a role in sustaining the main emotions in the play and maintaining the emotional balance between tragedy and comedy. These findings suggest that Beckett used pauses as an essential device for fine-tuning the emotional composition of the play. This study demonstrated the potential of deep learning-based emotion analysis to contribute to the interpretation of literary works and presented a new strategy for quantitatively analysing the emotional impact of non-linguistic elements such as pauses. Through this study, this research will expand the interface between emotion analysis and literary

studies and lay the foundation for future research to explore the role of pauses in various fields.

7.2 Limitations

Despite the valuable insights gained from this study, there are several limitations to the study. First, there is a possibility of bias in the dataset on which the emotion analysis model was trained. The GoEmotions dataset used as training data in this study is based on Reddit user comments, and all the emotion labelling tasks in the corpus were performed by English speakers from India.[8] In this respect, it is possible that the cultural background of the raters may have influenced their emotion classification, which in turn may limit the model's ability to learn more universal emotional expressions. Therefore, future research will need to design emotion analysis models to minimize specific cultural biases by building datasets that include another online communities' or social medias' comments and raters from diverse English-speaking backgrounds, even for English-based datasets. This will enable the development of emotion analysis models that can cover the emotions of a more diverse human population.

In addition, the process of deriving multiple labels was challenging. In the initial analysis of this study, a threshold of 0.5 and 0.3 was set for a single sentence to ensure that only emotions with a probability of at least 30% were output. However, in individual sentences, a single emotion often accounted for more than 30% of the probability, while the other emotions had relatively low percentages. In a subsequent reanalysis, all analyzed emotions in a sentence were sorted in descending order, and it was discovered that the second highest emotion could be interpreted as a semantically relevant emotion, even though it accounted for a single-digit percentage of the total. These observations suggest that there is a need for goal-oriented fine-tuning of how to set the emotion range in multi-label classification. In particular, while neutral emotions accounted for the highest proportion of pauses in this study, further analysis of the distribution of label confidence score is worthwhile. Future research will need

to explore how the way pauses modulate the flow of emotions can be reflected in advanced multi-emotion analyses.

7.3 Future work

In future research, there are a number of possible extensions to the findings of this study. First, it can be extended to other literary works. While this study focused on *Waiting for Godot*, it is worth examining whether pauses play a similar role in shifting emotions in Beckett's other plays, such as *Endgame* and *Happy Days*. Furthermore, research could explore how pauses differ in the way they modulate emotional flow compared to other playwrights' works where pauses are visibly represented.

Second, studies could attempt to extend the method to real human dialogue data. While this study was the emotion analysis based on literary texts, exploring how pauses relate to emotional expression in real human dialogue can also contribute to research in Affective Computing and Human-AI Interaction. Research that analyses the role of pauses in everyday dialogue to convey emotional tension, hesitation, or textual flow could be an invaluable contribution to expanding the applicability of emotion analysis methods to a variety of domains.

To conclude, this study is one of the first to quantitatively examine the role of pauses in literary texts using deep learning and emotion analysis. The results of the analysis showed that pauses function to sustain key emotions and maintain the emotional balance of the play. This is significant in that pauses tend to maintain a particular emotional state rather than induce emotional transitions and serve to reinforce the characteristics of the tragicomedy genre, which is a mixture of tragedy and comedy. This study provides a unique methodology for applying emotion analysis to literary studies and suggests that deep learning-based emotion analysis can be extended to include non-linguistic elements. Therefore, this study is expected to serve as a foundation for future research exploring the role of pause in literary texts.

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