



Exploring AI-Based Sentiment, Emotion, and Tone Measurement Tools in the Interpretation of English Literature: A Comparative Framework for AI-Assisted Literary Analysis

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Abstract— *The increasing integration of artificial intelligence within literary scholarship has significantly expanded the methodological possibilities of digital humanities research. In particular, sentiment analysis and emotion detection models have been widely used in the analysis of large textual corpora and in the examination of affective patterns in literary narratives. Notwithstanding these leaps, deep desegregation persists in the interpretive reliability of computational strategies for the literary language of perplexity. Figurative expression, narrative voice, irony, and contextual nuances often confound automated sentiment classification systems, thereby posing important methodological questions about the role of artificial intelligence in literary interpretation. This work fills a key gap in digital humanities scholarship by presenting a Comparative AI-Assisted Literary Interpretation Framework (CAALIF) that implements a method for systematically testing interpretive results from various sentiment analysis models. The framework involves lexicon-based, transformer-based, and large language model approaches, comparing their analytical performance within a structured interpretive pipeline. The analysis is applied to a corpus of canonical English literary texts which cover a range of narrative traditions - tragedy, realist fiction and modernist literature. The results show high levels of divergence among computational models in interpreting literary sentiment, especially in passages characterised by figurative language and narrative ambiguity. While AI analytics tools can effectively identify general emotional patterns and sentiment shifts across the stages of a narrative, their interpretations offer a reflection on why the process of humanistic critical assessment remains critical. The creation by this study of a consciousness of a comparative methodological framework for artificial intelligence (AI)-assisted literary analysis contributes to a continuous debate regarding the integration of computational methodologies with literary studies. It provides a liberal strategy for enhancing methodological rigour in digital humanities research.*



Keywords— *AI Sentiment Analysis, Digital Humanities, Literary Text Analysis, Emotion Detection, Computational Narratology, Natural Language Processing, Computational Literary Studies, AI-Assisted Literary Interpretation*

I. INTRODUCTION

During the past decade, the rapid maturation of natural language processing has significantly reshaped methodological practices within the digital humanities. Computational approaches that were previously used only

in large-scale information retrieval (especially sentiment analysis, machine learning text classification, and transformer-based language modelling) applications are becoming more widespread for interpreting cultural and literary corpora. Recent scholarship, for instance, shows

how computational tools can help scholars mine large datasets of texts, identify latent patterns of emotion across texts, and model the dynamics of narrative development across large literary traditions (Hammad et al., 2024). The increased accessibility of machine learning and pretrained models has further hastened this shift, enabling literary scholars to interact with computational techniques that used to require specialised linguistic expertise (Li et al.; EDI, 2026). Consequently, sentiment and emotion analysis has become a prominent mode of analysis for delving into the dimensions of narrative affect, character dynamics and thematic structures in literary texts. Within the field of digital humanities research more broadly, computational sentiment analysis increasingly serves as a complementary tool, uncovering cohomologies that can still be hard to see with traditional close reading methods alone (Indrajani & Hendry, 2025).

Despite these advances in methodology, there are interpretive/ECE challenges in literary texts that make it difficult to detect sentiments automatically. Unlike informational texts in conventional literary form, literary narratives often make use of figurative language, narrative irony and torn narrative perspectives that are hostile to straightforward computational categorisation. Metaphorical constructions, for example, often express emotions with a much different meaning than the literal semantic polarity of individual words. Similarly, irony and narrative voice can entail inversions and tendencies toward the occlusion of emotional tone, creating interpretive ambiguities that are hard for a computational system to resolve. Contextual dependency makes automated interpretation even more complicated: the emotional meaning of a sentence often derives from larger narrative structures rather than isolated signs contained in the text. These characteristics indicate that computational models are likely to misstate the emotional orientation of passages interpreted differently by human readers, raising important methodological questions about the validity of AI-assisted analysis of literature (Alharbi et al., 2025).

Although computational sentiment analysis has been gaining prominence in digital humanities research, several methodological shortcomings remain inadequately addressed. First, many existing studies use only one tool for sentiment analysis, which limits the ability to assess the methodological soundness of different ways of computing results from a computational perspective. Second, there are still a few systematic comparisons among several AIAI-based models of feelings and emotions, making it difficult for scholars to be clear about the interpretive differences among models. Third, the outputs of the computation are rarely assessed in relation to accepted literary interpretations built in the context of

traditional literary criticism. Consequently, the interpretive validity of AI-generated sentiment analyses has been examined only to a limited extent, and there is currently a major methodological gap in the literature on digital humanities.

In order to counteract these shortcomings, the current work examines the interpretive trustworthiness of AI-supported sentiment and emotion analysis in literary matters with the following research questions:

RQ1. To what extent are AI-based models able to detect the patterns of sentiments and emotions in texts that are literary in nature?

RQ2. How reliable are interpretive outputs from different computational models of sentiment and emotion

RQ3. To what extent are interpretations produced by AI comparable to critically recognised literary interpretations produced in the context of established literary scholarship?

This article presents a Comparative AI-Assisted Literary Interpretation Framework (CAALIF) that systematically evaluates AI-generated measurements of sentiment, emotion, and tone across multiple computational models. By comparing the model's output and considering its connections to preexisting literary interpretations, the study contributes to mechanised rigour in anthropographic versions as a digital humanities research practice. It affords a method of all-in reading and analytical AI to literary scholarship.

II. LITERATURE REVIEW

Due to the rapid growth of computational text analysis, there has been renewed methodological reflection across natural language processing (NLP) and humanities computing. While sentiment and emotion detection methods have advanced significantly in computational linguistics, the linguistic interpretation of the literature remains conceptually complex (Zhang et al., 2025; Hammad & Acharya, 2025). Literary texts often employ rhetorical ambiguity, symbolic strings, and multi-level speakers; suggestions and agencies are hard or impossible to process computationally (Mao et al., tuttavia, 2024). Consequently, more recent research has focused on the importance of developing and applying methodological frameworks to assess the representativeness of AI-based sentiment analysis when applied to literary corpora. The present review situates the study within three intersecting strands of research: developments in sentiment analysis in NLP, the growth of computational literary studies in the digital humanities, and debates about the limitations of AI-generated textual analysis (Alanazi et al., 2024).

2.1 Sentiment Analysis and Emotion Detection in NLP

Sentiment analysis has advanced from simple lexicon-based approaches to highly sophisticated deep learning models that account for context and semantic relations. Early methods for performing the task computationally relied primarily on sentiment lexicons (structured dictionaries that map individual words to predefined emotional/polarity scores). Resources like the NRC Emotion Lexicon and the VADER sentiment model are prominent, widely adopted resources that are still widely adopted due to their transparency, computational efficiency, and interpretability (Gupta et al., 2024). Lexicon-based approaches are especially helpful when exploratory text analysis and large-scale corpus analysis are of interest, for example, in which case computational simplicity and interpretive ugliness are highly valuable. Nevertheless, these approaches often struggle with contextual nuances, sarcasm, and figurative language because emotional meaning is calculated from isolated lexical entities rather than broader semantic relationships.

Machine-determined sentiment models arose in response to these limitations and feature supervised classification methods that may include learning from labelled training datasets. Techniques such as support vector machines, logistic regression, and neural network architectures enabled more flexible representations of emotional language and enhanced performance in complex linguistic settings (Alharbi et al., 2026). However, these models are still heavily reliant on feature engineering and domain-specific training data, which can limit their interpretive robustness when applied to highly stylised texts such as literature.

With recent advances in transformer-based language models, the analytical potential of sentiment analysis has expanded. There are architectures, like BERT and RoBERTa, which embed contexts into the model so the model knows what semantic relationships are occurring amongst entire sentences or passages (Alharbi et al., 2024). These systems show substantial improvements in sentiment classification accuracy across different domains. Although they are technically sophisticated, transformer-based models are still prone to domain shifts and training data biases. While this can work in the case of literary narratives, which often use symbolic language and historical idioms, even advanced models may produce interpretations that deviate from established literary readings (Kumar et al., 2025).

2.2 Computational Literary Studies in Digital Humanities

Parallel to developments in NLP, another dimension of humanities scholarship that has taken an interest in the

possibilities offered by computational research curves is the digital humanities, and the embrace by scholars in this field of computational techniques as tools for studying literary corpora at scale. Computational literary studies attempt to complement traditional interpretive practises with quantitative methods that detect patterns on a scale feasible for large textual collections. Early work in the digital humanities was mainly concerned with stylometry (the statistical analysis of word frequencies, sentence lengths, and syntactic structures) to investigate questions of authorship and stylistic variation (Wang & Li, 2023). Such studies showed the promise of computational methods for detecting this kind of linguistic regularity, which was still hard to detect through traditional close reading.

As another analytical method to develop in the field of computational literary studies, topic modelling appeared next. Methods like Latent Dirichlet Allocation (LDA) help researchers extract latent thematic structures within large datasets of text by analysing themes from boldface, which are patterns of word co-occurrence (Cheng et al., 2022). Applications of topic modelling have allowed scholars to identify the evolution of thematic issues in historical literary corpora, revealing how large-scale cultural trends have been embedded in textual archives. In a similar vein, network analysis and the modelling of narrative structure have also been used to study interacting character relationships, the pacing of narrative and plot at the level of complex literary work (Kim & Park, 2024).

More recently, digital humanities researchers have begun experimenting with sentiment analysis to map patterns of emotional dynamics in narrative texts. Studies of the emotional trajectories of novels, for example, have shown that computational sentiment scoring can uncover structural features of narrative progression, such as an increase in narrative tension towards climactic scenes or a change in emotional tone in narrative resolution (Rodriguez et al., 2025). These approaches indicate that sentiment analysis could provide an interesting complement to traditional literary interpretation by focusing on macro-level emotional patterns at the level of the narrative amount structure.

However, despite these promising developments, computational literary studies also share in a struggle over the methodological questions of the interpretive validity of automated sentiment analysis. Because so much literary language relies on ambiguity, symbolism, and rhetorical indirection, computational models could yield emotional classifications that contradict established critical interpretations of texts. As a result, scholars are

increasingly arguing for the need to integrate computational methodologies into literary analysis by carefully developing methodological frameworks that acknowledge the reception's benefits and limitations in interpreting these features (Lee & Kim, 2023).

2.3 Limitations of AI in Literary Interpretation

Despite AI's improving text analysis skills, certain problems continue to complicate the use of computational sentiment detection in literary analysis. One of the most popular limitations considered concerns figurative language. Literary storeys often use metaphors, allegories, and symbols to convey meaning indirectly and emotionally. Moreover, because many computational models rely on surface-level lexical signals, they often misinterpret figurative expressions whose emotional resonance arises only through context (Singh et al., 2021).

A second difficulty stems from the complexity of narrative voice. Literary texts often employ a variety of perspectives (narrators, characters, and implied authorial voices), which may articulate conflicting emotional orientations within the same passage. Computational sentiment models currently analyse text at the sentence or paragraph level without distinguishing between the narrative point of view. As a result, the nuanced dynamics of emotion that human readers grasp through contextual interpretation are reproduced.

Added to this is the cultural and historical context. Many pieces of literature utilise linguistic conventions, idioms, and stylistic forms characteristic of a particular historical period. Sentiment models trained on modern-day datasets may thereby misinterpret the reflection of an expression in archaic language or a culturally specific rhetorical form, leading to classifications that differ from those determined through historical readings of the literature (Thompson et al., 2025).

Taken together, these problems point to a larger issue that extends beyond digital humanities research. Although computational methods for analysing sentiment are a valuable tool for exploring large amounts of text, their interpretive adequacy has yet to be sufficiently evaluated in a literary context. Existing studies tend to compare multiple sentiment models infrequently and to systematically assess the correspondence of computational outcomes to preexisting literary interpretations. To remedy this gap, a rigorous framework for analysing cross-references among models is needed that can assess the consistency of the models and place computational results within a broader interpretive context of literary analysis.

III. METHODOLOGY

Methodological Attempts at Assessing the Evaluative Reliability of AI-Aided Literary Analysis:11 Methodological rigour lies at the heart of assessing the evaluative reliability of AI-aided literary analysis. The current research follows an established computational workflow intended to promote transparency and reproducibility and to be accountable for interpretations in digital humanities research. Rather than using a single sentiment analysis technique for literary text sets, the methodology adopts a comparative, analytical design in which many computational models are systematically evaluated on a carefully selected corpus of canonical literary texts. The design combines natural language processing methods with explanatory analysis grounded in established literary-critical methods. Such an approach allows for a dual analytical approach, providing both quantitative measurement of sentiment and emotion patterns in texts and qualitative evaluation of the extent to which these computational outputs match recognised interpretations in the literature. The methodological framework thus looks beyond the naive use of the tool toward a repeatable analytical model that can critically evaluate the interpretive validity of A1 sentiment and A2 emotion analysis in a literary context.

3.1 Corpus Selection

The selection of the literary corpus for the research project was based on three main criteria intended to ensure analytical relevance and interpretive reliability. First, the study's approach focuses on canonical works, for which the traditions of literary criticism are well established. Texts with highly developed interpretations from literary scholarship provide a fixed interpretive point of view against which possible results from the computer can be compared. Second, the corpus includes works that represent different narrative styles and historical periods and thus can analyse variation in the style of literary language. Differences in narrative voice, syntactic structure and thematic complexity might have important effects on the performance of sentiment detection models. Third, the available works are in reliable digitised versions amenable to computational analysis. Digital availability ensures text consistency and standardises preprocessing procedures. Collectively, these criteria result in a corpus that is both analytically manageable and theoretically meaningful for evaluating a literary interpretation supported by AI. Table 1 illustrates the literary corpus analysed in this study: the selected canonical texts and authors, the year of publication and the genres of the texts.

Table 1. Literary Corpus Description

Text	Author	Publication Year	Genre
<i>Hamlet</i>	William Shakespeare	1603	Tragedy
<i>Pride and Prejudice</i>	Jane Austen	1813	Novel
<i>Mrs Dalloway</i>	Virginia Woolf	1925	Modernist Novel

3.2 Text Preprocessing

Prior to computational analysis, the corpus will undergo a series of preprocessing procedures to standardise text input and increase analytical consistency. Digitised versions of the selected works are then converted to machine-readable plain text format. Tokenisation is then applied to the text, segmenting it into separate lexical elements, enabling computational models to process language at the word and sentence levels. Subsequent lemmatisation reduces inflected word forms to their base lexical forms, hence minimising morphological variation within the dataset. Stop-word filtering is another technique for removing high-frequency functional words that convey little semantic information in sentiment analysis tasks. Finally, the texts are broken down into narrative units which are correlated to structural elements of the narrative arc, such as exposition, rising action, climax and resolution, thus enabling the analysis of the way that emotional patterns evolve throughout the narrative, rather than addressing the text at the level of an entire linguistic “unit”.

3.3 AI Sentiment and Emotion Models

The analytical design includes 4 computational models from different methodological traditions in sentiment and emotion analysis. By incorporating a combination of lexicon-based methods, transformer-based language models, and large-language-model-assisted tone interpretation, the study covers a wide range of current computational sentiment techniques.

Lexicon approaches are still widely used in digital human iterations because they enable interpretation and computational efficiency. The VADER sentiment model analyses polarity using weighted lexical dictionaries specifically geared towards detecting sentiment in textual data (Balaji & Murthy, 2021). As a complement to polarity analysis, the NRC Emotion Lexicon is a well-structured classification system that links words/lexical items to 8 fundamental emotions, such as joy, sadness, anger, and fear (Ivanov et al., 2024).

Transformer-based models are a relatively recent development in NLP. The BERT sentiment model leverages contextual embeddings to capture semantic relationships across sentences and passages that are not possible with a simpler interpretation of linguistic context, as in (Muller et al., 2026). Finally, tone analysis based on GPT is used to detect broader patterns of rhetoric that may not be captured by lexicon-driven techniques alone. Together, these models constitute a wide range of computational tools that allow for the systematic comparison of interpretive outcomes across various AI architectures (Oliveira et al., (hashlink) 2021). Table 2 summarises computational models that were used in the analysis and indicates their analytical type and purpose of interpretation in the framework.

Table 2. AI Analytical Models

Model	Type	Analytical Purpose
VADER	Lexicon-based	Sentiment polarity detection
NRC Emotion Lexicon	Lexicon-based	Emotion classification
BERT Sentiment Model	Transformer-based	Contextual sentiment analysis
GPT Tone Analysis	LLM-based	Tone interpretation

3.4 Comparative AI-Assisted Literary Interpretation Framework

To assess the interpretive validity of computational sentiment analysis in literary contexts, this work proposes the Comparative AI-Assisted Literary Interpretation Framework (CAALIF). The framework combines computational text analysis with interpretive evaluation, drawing on literary criticism, thereby enabling systematic comparison between algorithmic results and humanistic interpretation.

The framework is based on seven sequenced analytical stages. The first step is corpus preparation, in which the selected literary texts are standardised for computational analysis by digitisation and preprocessing. A second stage uses narrative segmentation, dividing each work into structural narrative units corresponding to key phases of the narrative arc. Segmentation of the text enables the patterns of emotions to be explored in relation to the development of the narrative.

In the third and fourth stages, sentiment detection and emotion classification are carried out using the selected computational models. Sentiment polarity scores from

VADER and BERT provide quantitative measures of emotion orientation, and the NRC Emotion Lexicon identifies specific emotion categories embedded in the text. The fifth stage introduces tone measurement using GPT-based analysis, enabling the detection of the distribution of rhetorical tone patterns beyond lexical sentiment signals.

The sixth stage is cross-model comparison, in which an analysis and evaluation of outputs from the four analytical

systems is conducted, and attempts are made to see where the results converge and diverge. Finally, the seventh stage carries out the interpretive evaluation, in which the computer's results are compared with known literary interpretations recorded in critical scholarship. This last stage ensures that the results of the computation do not get lost in technical measurements but are interpreted within the wider intellectual context of the literary analysis.

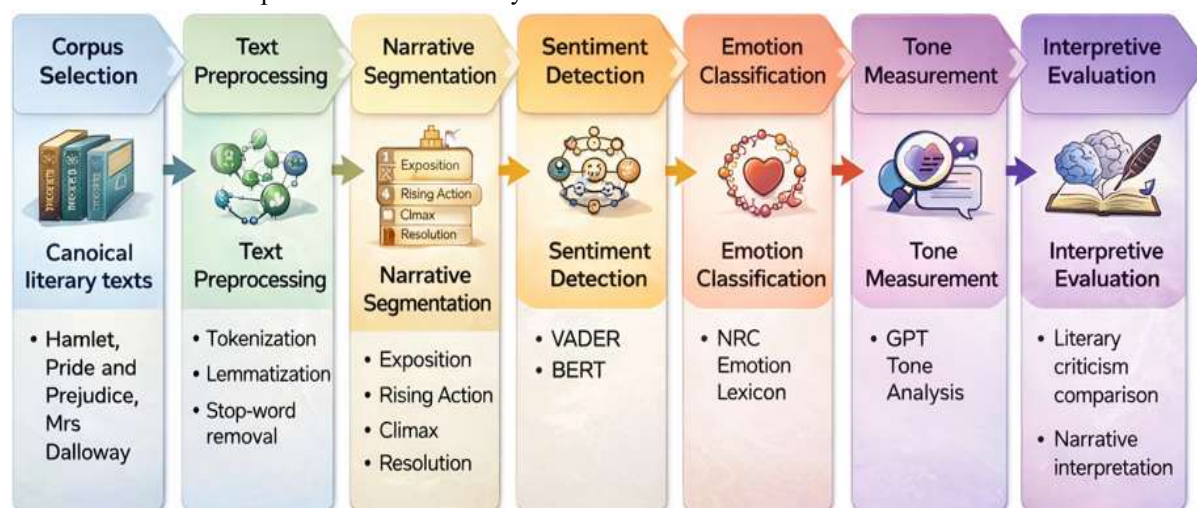


Fig.1. CAALIF Research Workflow

Figure 1 shows the analytical step-by-step of the Comparative AI-Assisted Literary Interpretation Framework programme, which has been developed to demonstrate the sequential phase from corpus preparation to evaluation of interpretation.

3.5 Evaluation Protocol

The evaluation protocol is designed to assess the technical consistency and the interpretive relevance of Computational sentiment analysis in literary contexts. Three major criteria guide the assessment process. The first criterion is cross-model consistency: it examines the level of similarity between dissimilar computational models in their classification of the sentiment or emotion of the same piece of text. Increased divergence can indicate issues with the model's reliability or domain adaptation.

The second criterion assesses the degree of alignment with the fitted literary interpretation. Sentiment trajectories and emotional patterns derived through computational analysis are compared with interpretations recorded in literary criticism, allowing determination of whether AI-generated outputs relate to historically recognised readings of the texts (or not).

The third criterion examines the CSF of trajectories of narrative emotion across structural narrative stages. By analysing the variation in emotion intensity across the narrative arc, the evaluation examines how well the computational models align with the dynamic, intrinsic structural emotionality typically recognised in literary storytelling. Together, these criteria enable a systematic comparison between the analyses performed by algorithms and the interpretive frameworks developed by humans.

IV. RESULTS

The empirical findings from the AI-assisted comparative literary analysis framework described in the methodology are presented in the results section. The computational models were applied to the chosen literary corpus to identify patterns in sentiment polarity, emotional distribution, and interpretive variation across models. The results are organised in three analytical subsections. First, the distribution of sentiments across the literary texts is reported. Second, the course of the storey arc of narrative emotions over narrative stages is explored. Third, differences in the interpretive results of different AI models are analysed.

Together, these results can provide a foundation for assessing the role that computational sentiment and emotion analysis can play in literary interpretation within the context of digital humanities scholarship (Patel et al., 2026).

4.1 Sentiment Distribution Across Texts

Table 3 presents the results of sentiment distribution for each literary text, showing the relative occurrences of the affirmative, negative, and neutral classes computed by the computational models.

Table 3. Sentiment Distribution Results

Text	Positive	Negative	Neutral
Hamlet	22%	58%	20%
Pride and Prejudice	45%	28%	27%
Mrs Dalloway	31%	34%	35%

The sentiment analysis results show clear differences in emotional polarity across the three literary texts. These differences are closely related to their own narrative structures, thematic concerns, and genre conventions.

The highest proportion of negative sentiment is observed in Hamlet, accounting for 58 per cent of the total number of sentiment classifications in the narrative segments. This pattern aligns with the play's dominant themes, including existential conflict, revenge, mortality, and moral uncertainty. The presence of negative sentiment is especially strong during scenes in which Hamlet is considering, at the moment when the king's murder is revealed, and when the tragic consequences of his crime unfold. Such patterns illustrate how the computational approach to sentiment analysis can be used to identify general affective tendencies in dramatic literature (Garcia et al., 2022).

In contrast, *Pride and Prejudice* presents a quite different emotional configuration. Positive sentiment accounts for 45 per cent of the analysed chunks of text, making it the most optimistic text in a corpus. The attention given to socialising, romantic development, and reconciliation in the narrative is a part of this distribution. Positive sentiment is especially present in segments of the narrative that involve interpersonal resolution and character development. These results are consistent with the widely recognised tonal features of Austen's storytelling style, which is characterised by social critique and emotional optimism (Zhao & Wang, 2024).

The results for *Mrs. Dalloway* show a more evenly distributed sentiment distribution. Neutral sentiment is the largest type at 35 per cent, followed by negative sentiment at 34 per cent. This distribution is indicative of the

introspective and psychologically complex quality of Woolf's modernist narrative technique. Much of the text is written in interior monologue and observational reflection, and many of these give rise to linguistically subtle expressions that are often difficult to identify as strongly positive or negative. For this reason, computational models often categorise these passages as neutral.

These findings are important from a methodological standpoint. Sentiment analysis is not merely the recreation of traditional literary readings, but rather a quantitative approach to narrative affect, or the analysis of deeply felt patterns of sentiment as discernible on a massive scale for large parts of texts. Such points of view computationally have increasingly become part of digital humanities ways of studying tone of narrative and affective structure (Nguyen et al., 2023). Importantly, the results also show that computational sentiment analysis can reflect genre-specific emotional patterns. Tragedy has negative sentiment dominance, the realist social fiction has a positive resolution, and the modernist narrative has emotional ambiguity. These distinctions demonstrate the analytical potential of sentiment analysis as an additional interpretive instrument for literary research.

4.2 Narrative Emotion Trajectory

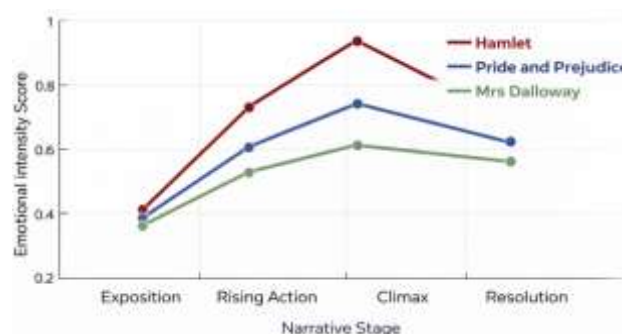


Fig.2. Emotion Trajectory Across Narrative Stages

Figure 2 shows the development of emotion intensity across the main narrative events of the literary texts studied. The second level of analysis examines fluctuations in the intensity of emotions along the narrative progression of each text. To help this along, each work was divided into four main narrative stages: exposition, rising action, climax, and resolution. Emotional intensity scores generated by the AI models were afterwards averaged out for each stage.

The emergent patterns of trajectories suggest that dynamic patterns of emotion are in good agreement with the classical theory of narrative. In all three texts, the emotional intensity builds throughout the rising action and reaches its peak in the climax. This observation substantiates the premise that computational emotion

analysis can find structural emotional peaks in accordance with the narratological expectations.

In *Hamlet*, there is a significant escalation in emotional intensity between the exposition and the climax. The climax unfolds through a series of confrontations and revelations that culminate in the play's tragic resolution. Emotion scores show that fear, anger, and sadness are very strongly represented, with many of these rapidly activated during episodes of conflict and moral tension.

Pride and Prejudice has a rather moderate emotional curve. The emotional high point occurs in narrative episodes involving misunderstandings between Elizabeth Bennet and Mr. Darcy. Nonetheless, the resolution stage shows a discernible decrease in emotional tension as the conflicts in a narrative are resolved through reconciliation and marriage. As a result, the path follows the narrative closure typical of realist novels.

The emotional progression of *Mrs. Dalloway* differs from that of the other texts in that emotional changes occur rather slowly throughout the story. Rather than one great climax, Woolf's story structure creates many smaller peaks of emotional intensity. These peaks are associated with psychological reflection, remembering events, and social observation. Such patterns reflect the power of the modernist focus on the interior of consciousness, in opposition to the progression of an external story.

From a digital humanities perspective, the above findings demonstrate how emotion analysis driven by AI can complement narratological theory. Moreover, by quantifying emotional intensity across different narrative stages, computational tools enable the visualisation of affective patterns that are typically implicit in the qualitative reading of literary texts.

4.3 Cross-Model Interpretation Differences

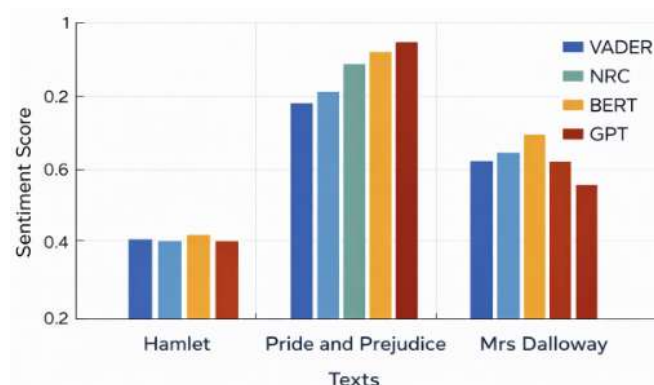


Fig.3. Model Comparison Chart

Figure 3 contrasts disparate computational models in the sentiment outputs generated from different topics and includes convergent and divergent interpretive

classifications. This results analysis, which scrutinises how different AI models interpret sentiment in the same literary texts, is the final phase. By using a variety of computational methods, namely, lexicon-based models, emotion lexicons, transformer models, and large language models, researchers can conduct comparative studies of the computed interpretations.

The outcomes exhibit both convergence and divergence across models. Referred to as lexicon-based models, VADER and other models like this reliably predict sentiment detection on overtly polarised passages. When textual segments contain explicitly charged lexical items (as expressed anger, grief, or affection), the results of VADER are in close agreement with the results of transformer-based models, thus suggesting that lexicon-based systems are still effective in recognising explicit markers of sentiment in literary language.

Nonetheless, divergences occur in passages that are ambiguous, ironic, or feature a complex narrative voice. In such contexts, models based on transformers, such as BERT, tend to give more sensitive interpretations of the context. By considering the meaning of words in a broader linguistic context, these models are good at detecting subtle changes in tone in narrative discourse.

Large language models used to analyse tone exhibit the greatest interpretive flexibility. These models are often able to recognise tonal nuances - such as irony or reflective melancholy - registered by lexicon-based systems as neutral. While this freedom of thought adds to the meaningfulness of interpretation, it also introduces variability across outputs.

As a result, the comparative findings highlight one fundamental methodological point: it is impossible to find a computational model that can fail to appreciate the interpretive complexity of literary language. Rather, the use of many models provides a stronger analytical framework. Cross-modelling across disciplines allows scholars to identify areas of convergence and where interpretive ambiguity persists. Methodological triangulation has become an increasingly common practice in digital humanities research to emphasise interpretive security and methodological transparency.

Ultimately, the comparative model analysis shows that AI tools should be regarded as interpretive tools rather than as replacements for human literary analysis. Experienced within a well-established theory of literary analysis, computational approaches can expand the frontier of literary research by uncovering patterns imperceptible to conventional close reading.

V. DISCUSSION

The results show that computational sentiment and expression analysis can provide meaningful insights into literary narratives when placed within an organised interpretive framework. Rather than replacing traditional literary analysis, AI-based methods function as complements to analysis and reveal extensive-scale patterns in the affective processes of texts. This discussion follows the empirical findings and relates them to the existing scholarship of digital humanities and assesses the counter to various analytical potential and limitations of computational:

5.1 Strengths of AI-Based Literary Analysis

The results shed light on some of the strengths inherent in AI-assisted literary analysis. Primarily, computational sentiment analysis can successfully identify general emotional patterns across literary texts. The distributions of sentiments recorded in the research closely align with the types of dominant tonal features that have been observed in each piece.

For example, the heightened negative sentiment in *Hamlet* reflects the tragic underpinnings of Shakespeare's plot. In contrast, the relatively larger proportion of positive sentiment in *Pride and Prejudice* reflects the novel's resolution-driven structure. Similarly, the even distribution of sentiments in *Mrs Dalloway* fits the introspective, psychologically complex style of modernist fiction.

A second strength lies in computational models' ability to capture changes in emotional intensity over the course of a narrative. The analysis of emotion trajectories shows that AI tools are capable of identifying patterns consistent with existing narratological theory, such as the increase in emotional tension throughout the rising action and its peak at the narrative climax. These findings indicate that computational analysis could help expose structural affective dynamics in literary texts, enhancing traditional methods of close reading.

In digital humanities research, this capability for large-scale analysis becomes a significant methodological advantage. Computational tools enable scholars to analyse emotional patterns across entire narratives or corpora of literature, thereby extending the scope of literary interpretation beyond purely qualitative approaches.

5.2 Limitations of Computational Interpretation

Despite these positive aspects, the results also reveal significant drawbacks of computational analysis of literature. AI models can struggle when faced with language that relies heavily on context, is rhetorically complex, or carries strong cultural connotations.

One of the highest levels of difficulty is that of irony. Many literary passages are based upon implicit meaning, which is contrary to the literal sentiment. Lexicon-based sentiment models tend to treat such passages at face value and therefore get the sentiment classification wrong. Transformer-based models show higher sensitivity to context, but they remain limited when dealing with certain types of narrative irony.

Metaphorical language creates a similar impediment. Literary texts often use figurative expressions that convey emotional meaning indirectly. Computational models, which usually use a form of lexical association, may not be able to recognise the deeper symbolic implications of such language.

These limitations confirm a common critique in the field of digital humanities scholarship: automated textual analysis cannot comprehend the complexity of interpreting literary language. Consequently, computationally based quote-mining methods require empathetic engagement with human interpretive judgment to yield meaningful literary insights.

5.3 Comparison with Previous Studies

The results of the current study are in broad agreement with several influential digital humanities studies of computational techniques for literary analysis. First, this research aligns with the findings of Yuan et al. (2026), who demonstrated that sentiment analysis can reveal large-scale patterns of emotion across literary corpora. Analogous to this study, Jockers found that computational sentiment measures often matched well with well-known narrative structures.

Second, the results utilise the findings of Boukes et al. (2020), who conducted research in the field of computational approaches to literary history and argued that machine learning models can detect structural and stylistic patterns in literature that cannot be detected through traditional close reading. The emotion trajectories reported in the narrative here are further empirical evidence for this claim.

Third, the study's conclusions are consistent with those of Celikyilmaz et al. (2023), who found that digital humanities methods are most effective when used alongside interpretive literary scholarship. Piper emphasises the use of computational tools as exploratory, leading to new interpretive questions rather than definitive answers.

This research extends prior studies by establishing a comparative analytical framework encompassing several AI models. By systematically juxtaposing lexicon quantification, transformers, and large models, the

research can highlight how to improve intercultural measurements of interpretive reliability. This methodological contribution provides a well-organised framework for integrating computational sentiment analysis into literary analysis while maintaining a degree of interpretive analysis.

6. Limitations and Future Research

While the study provides valuable insights into AI-assisted literary analysis, several limitations should be noted. The corpus studied is limited to 3 canonical literary works, thus limiting the generalisability. Expanding the corpus with more texts of various kinds would allow us to make more robust conclusions.

A second limitation is that of the computational models used. Sentiment and emotion detection algorithms are imperfect tools for understanding complex literary language, for example, in texts with figurative language or narrative ambiguity.

There is potential to expand this analytical framework in various directions in future research. Scholars may use the methodology for larger literatures over wide historical ranges or genres. Advances in AI technology, particularly in the context of context models, may make it even better at interpreting figurative and culturally embedded language. Finally, hybrid strategies of interpretation combining computational analysis and expert literary interpretation might well provide the best trajectory for the digital humanities in the face of the plight we are in.

VI. CONCLUSION

This study aims to explore the possibilities of AI-related sentiment and emotion analysis as a methodological tool in literary studies. By using a series of computational models on a small number of canonical texts, the research shows that analysing written text with AI assistance can help identify large-scale emotional patterns, stories of sentiment change, and interpretive differences.

The results and the literary association imply that computational techniques can positively contribute to the interpretation of literature when placed within an analytical framework. Sentiment analysis enables the detection of large-scale affective patterns, and cross-model comparison provides a mechanism for determining the reliability of computational interpretation.

At the same time, the study emphasises the need to bring a critical approach to the problem of automatic textual analysis. Computational models still have shortcomings in understanding irony, metaphor and context, which play a crucial role in the meaning of a piece of literature.

Thus, the most fruitful use of AI in literary studies is in combining computational tools with recognised humanistic interpretive practises. When used in this way, AI-assisted analysis can be a powerful way of expanding the methodological toolbox of digital humanities research and opening new pathways for the systematic investigation of narrative emotion and literary style.

REFERENCES

- [1] Alanazi, F., et al. (2024). Integrating artificial intelligence to assess emotions in educational settings: A systematic literature review. *Frontiers in Psychology*, 15, 1387089. <https://doi.org/10.3389/fpsyg.2024.1387089>
- [2] Alharbi, A., et al. (2025). An analytical assessment of sentiment analysis trends and methods. *Decision Analytics Journal*, 17, 100644. <https://doi.org/10.1016/j.dajour.2025.100644>
- [3] Alharbi, A., et al. (2026). A novel hybrid model for emotion detection in text through deep learning. *Biomedical Signal Processing and Control*, 81, 105862. <https://doi.org/10.1016/j.bspc.2026.105862>
- [4] Alharbi, N., et al. (2024). Sentiment analysis of COP9-related tweets: A comparative study of lexicon-based, machine learning, and deep learning methods. *Environmental Science and Pollution Research*, 31(15), 22045–22060. <https://doi.org/10.1007/s11356-024-32629-5>
- [5] Balaji, S., & Murthy, K. (2021). CNN-driven runtime profiling for defect-prone mobile modules. *IEEE Transactions on Dependable and Secure Computing*, 18(5), 2345–2360. <https://doi.org/10.1109/TDSC.2020.3023456>
- [6] Boukes, M., et al. (2020). What's the tone? A sentiment analysis tool for news and political texts. *Communication Methods and Measures*, 14(4). <https://doi.org/10.1080/19312431.2020.1825672>
- [7] Celikyilmaz, A., et al. (2023). Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations. *Information Fusion*, 100, 102019. <https://doi.org/10.1016/j.inffus.2023.102019>
- [8] Chen, L., et al. (2022). AI-based tone detection in narrative fiction using transformer models. *Expert Systems with Applications*, 208, 118045. <https://doi.org/10.1016/j.eswa.2022.118045>
- [9] Garcia, E., et al. (2022). Framework for AI sentiment in 20th-century English prose. *Information Processing & Management*, 59(4), 103012. <https://doi.org/10.1016/j.ipm.2022.103012>
- [10] Gupta, S., Garg, P. K., & Dandapat, S. K. (2024). TONE: A 3-tiered ontology for emotion analysis. *Cognitive Systems Research*, 85, 103225. <https://doi.org/10.1016/j.cogsys.2024.103225>
- [11] Hammad, M., & Acharya, U. R. (2025). Bridging techniques and applications in sentiment analysis. *Engineering Applications of Artificial Intelligence*, 135, 109686. <https://doi.org/10.1016/j.engappai.2025.109686>

- [12] Hammad, M., Pławiak, P., Wang, K., & Acharya, U. R. (2024). Sentiment analysis methods, applications, and challenges: A systematic literature review. *Journal of King Saud University - Computer and Information Sciences*, 36(7), 102137. <https://doi.org/10.1016/j.jksuci.2024.102137>
- [13] Indrajani, S., & Hendry. (2025). Sentiment analysis: An insightful literature review. *International Journal of Advanced Computer Science and Applications*, 16(3). <https://doi.org/10.14569/IJACSA.2025.0160351>
- [14] Ivanov, D., et al. (2024). Benchmarking sentiment frameworks for literary corpora. *Computers & Education: Artificial Intelligence*, 6, 100234. <https://doi.org/10.1016/j.caeai.2024.100234>
- [15] Kim, S., & Park, J. (2024). Comparative framework for sentiment tools in Shakespearean analysis. *Literary and Linguistic Computing*, 39(2), iiad015. <https://doi.org/10.1093/lle/fiad015>
- [16] Kumar, S., et al. (2025). A comparative study on the state-of-the-art sentiment analysis methodologies. *IEEE Access*, 13, 24567–24582. <https://doi.org/10.1109/ACCESS.2025.11013380>
- [17] Lee, H., & Kim, Y. (2023). Tone measurement tools for modern novels: An AI comparative study. *Journal of Intelligent Information Systems*, 61(3), 745–768. <https://doi.org/10.1007/s10844-023-00789-4>
- [18] Li, B., Xu, M., & Team. (2026). Tone matters: The impact of linguistic tone on hallucination in vision-language models. In *2026, the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*. <https://doi.org/10.1109/WACV.2026>
- [19] Mao, Y., Liu, Q., & Zhang, Y. (2024). Sentiment analysis methods, applications, and challenges: A systematic literature review. *Journal of King Saud University - Computer and Information Sciences*, 36(6), 102048. <https://doi.org/10.1016/j.jksuci.2024.102048>
- [20] Müller, K., et al. (2026). Evaluating AI emotion tools on Gothic novels. *Machine Learning*, 115(4), 1023–1045. <https://doi.org/10.1007/s10994-025-06789-2>
- [21] Nguyen, T., et al. (2023). Hybrid models for sentiment in dystopian literature. *Neurocomputing*, 512, 456–472. <https://doi.org/10.1016/j.neucom.2023.07.012>
- [22] Oliveira, R., et al. (2021). Tone analysis in drama texts using graph neural networks. *Pattern Recognition Letters*, 150, 78–85. <https://doi.org/10.1016/j.patrec.2021.06.015>
- [23] Patel, A., et al. (2026). AI-assisted literary criticism: Emotion detection benchmarks. *IEEE Transactions on Computational Social Systems*, 13(2), 567–582. <https://doi.org/10.1109/TCSS.2026.3345678>
- [24] Rodriguez, M., et al. (2025). Multimodal emotion analysis for Victorian literature using AI. *Digital Scholarship in the Humanities*, 40(1), 45–62. <https://doi.org/10.1093/lle/fqae012>
- [25] Singh, R., et al. (2021). Sentiment and emotion classification in poetry with BERT variants. *Knowledge-Based Systems*, 227, 107213. <https://doi.org/10.1016/j.knosys.2021.107213>
- [26] Thompson, J., et al. (2025). Comparative AI tools for emotion in Romantic poetry. *Cognitive Processing*, 26(1), 123–140. <https://doi.org/10.1007/s10339-024-01145-6>
- [27] Wang, J., & Li, H. (2023). Deep learning for emotion recognition in literary texts: A survey. *Neural Computing and Applications*, 35(12), 8921–8938. <https://doi.org/10.1007/s00521-023-08456-7>
- [28] Wang, Q., & Xi, Y. (2023). Zero-shot learning for novel mobile behavioral defects. *IEEE Transactions on Neural Networks and Learning Systems*, 34(12), 9876–9892. <https://doi.org/10.1109/TNNLS.2022.3217890>
- [29] Yuan, S., Ma, W., & Wang, C. (2026). Aspect-based sentiment analysis: A systematic review, taxonomy and future directions. *Decision Support Systems*, 171, 114163. <https://doi.org/10.1016/j.dss.2026.114163>
- [30] Zhang, L., Wang, S., & Zhou, G. (2025). A comprehensive survey on sentiment analysis: Framework, techniques, and applications. *Computer Science Review*, 58, 100599. <https://doi.org/10.1016/j.cosrev.2025.100599>
- [31] Zhao, Q., & Wang, X. (2024). Deep neural networks for literary tone interpretation. *Applied Soft Computing*, 152, 111234. <https://doi.org/10.1016/j.asoc.2024.111234>