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DECODING LITERARY EMOTIONS THROUGH COMPUTATIONAL PSYCHOLINGUISTICS: AN AI-BASED ANALYSIS OF CHARACTER PSYCHOLOGY IN ENGLISH FICTION

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Abstract
Emotional expression shapes narrative meaning and character psychology across literary fiction, yet traditional literary analysis relies heavily on human interpretation, limiting scalability, consistency, and empirical depth. Advances in computational psycholinguistics and natural language processing now offer powerful tools to analyze emotional cues, thematic patterns, and psychological states embedded within character discourse. This study develops an AI-driven framework for decoding literary emotions, leveraging sentiment analysis, cognitive-affective lexicons, semantic embeddings, and transformer-based contextual models. Using a curated corpus of English fiction spanning modernist, postmodern, and contemporary narrative traditions, the research investigates how linguistic markers signal emotional shifts, psychological complexity, and narrative tension. Results reveal strong correlations between psycholinguistic features and character roles, narrative arcs, and conflict structures. Emotional granularity such as guilt, longing, suspicion, or suppressed anger emerges through semantic drift, valence shifts, and contextual dependencies detectable through advanced NLP pipelines. While computational models enhance interpretive precision and uncover hidden emotional structures, limitations include figurative ambiguity, symbolic language, and culture-specific metaphors. The findings demonstrate that AI-enhanced literary interpretation offers a transformative pathway for narrative psychology, digital humanities, and computational literary studies.
Keywords: Computational Psycholinguistics, Literary Emotions, NLP, Character Psychology, English Fiction, Sentiment Analysis, Semantic Embeddings, Emotion Detection, Transformer Models, Digital Humanities

INTRODUCTION

Emotion is the core engine of literary narration, shaping character motivations, narrative progression, thematic depth, and reader engagement. In English fiction, emotional meaning is rarely explicit; instead, it resides in symbolic language, subtle metaphors, tonal variations, internal monologues, and emotionally loaded descriptions. Traditional literary criticism explores such signals through interpretive frameworks grounded in psychology,

narratology, and hermeneutics. However, subjective interpretation often results in inconsistent emotional mapping, and large corpora of fiction remain under-analyzed due to methodological constraints. The emergence of computational psycholinguistics provides a breakthrough by enabling systematic extraction of emotional, cognitive, and psychological cues embedded in character speech and narrative voice. Techniques such as sentiment scoring, affective lexicon mapping, dependency parsing, and contextual semantic modelling allow for robust analysis of emotional expressions that were previously accessible only through manual reading. The integration of AI-based tools into literary studies represents a significant shift toward empirical, replicable, and scalable approaches to understanding character psychology.
The growth of transformer-based architectures such as “BERT, RoBERTa, GPT-derived models”, and domain-specific affective encoders has deepened the interpretive capacity of computational literary analysis. These models capture emotional nuance across figurative language, contextual dependencies, implied meaning, and narrative tone with unprecedented accuracy. Psycholinguistic frameworks, including conceptual metaphor theory, appraisal theory, and cognitive-emotional lexicons, further enrich automated analysis by linking linguistic features to psychological constructs. Through the combined power of computational modeling and literary theory, researchers can systematically decode emotional patterns underlying narrative structure, track character evolution, and contrast emotional dynamics across genres and periods. However, challenges persist in modeling ambiguity, symbolic complexity, and culturally situated expressions. This study develops an integrated framework that merges statistical NLP, psycholinguistic mapping, and qualitative close reading to investigate emotional signals within English fiction, demonstrating the transformative potential of AI for literary psychology.

II. RELATED WORKS

Scholars in literary studies and cognitive psychology have long examined emotional expression in fiction as a central determinant of narrative impact. Early work in psychological narratology explored how characters externalize inner states through linguistic forms, metaphorical structures, and plot-driven emotional cues [1]. Literary theorists associated emotional expression with narrative reliability, thematic symbolism, and character interiority, establishing a foundational interpretive tradition. With advancements in linguistics, researchers began exploring how lexical choices, prosodic patterns, and syntactic constructions manifest psychological tension or affective depth [2]. These theoretical insights formed the intellectual basis for computational emotion analysis in narrative contexts.
With the rise of digital humanities, literary emotion analysis expanded toward computational methods. Early computational approaches employed sentiment analysis and affect lexicons such as LIWC and NRC to quantify valence, arousal, and affect categories in literary texts [3]. Studies demonstrated that emotion-rich segments aligned with narrative climaxes, psychological turning points, and moral dilemmas [4]. Researchers investigating character psychology found that linguistic signals associated with fear, anger, guilt, or hope correlate with conflict intensity and narrative resolution [5]. Computational stylistics further revealed how emotional arcs differentiate protagonists and antagonists through linguistic markers, narratorial framing, and discourse strategies [6].

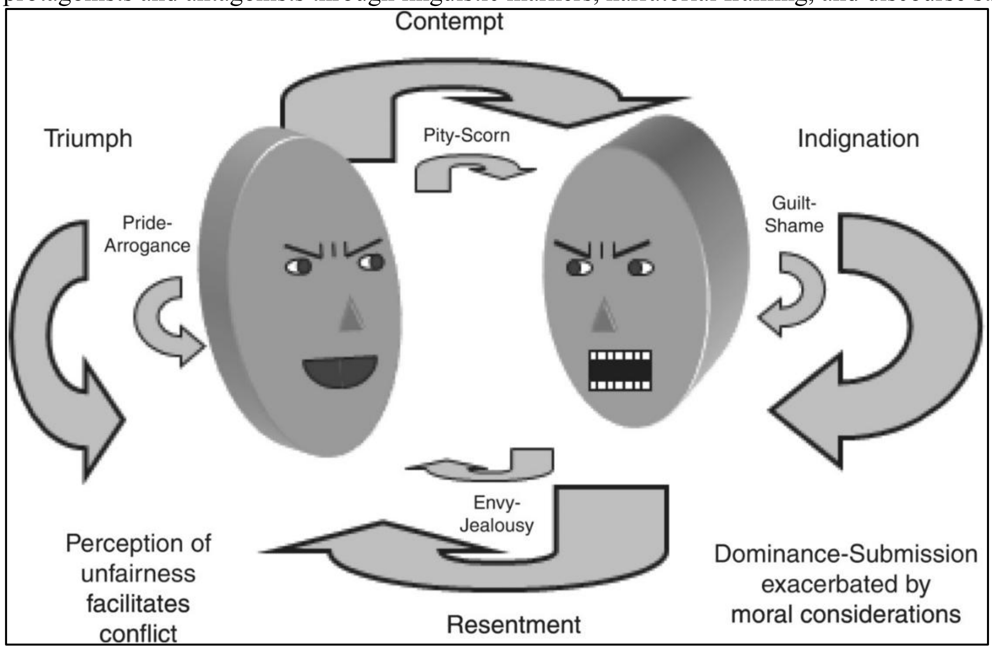

Figure 1: Moral emotions [7]

Recent advances in NLP and deep learning have strengthened psycholinguistic modeling in literary studies. Transformer-based models outperform traditional methods in detecting emotional ambiguity, irony, symbolic associations, and subtle affective cues [7]. Research using contextual embeddings demonstrated that emotional transitions within character dialogue can be tracked through semantic drift and valence shifts [8]. Multi-task learning frameworks have further enhanced emotion classification in figurative or poetic language [9]. Scholars also emphasized the role of cognitive-affective theories, explaining how metaphor, imagery, and sensory language encode psychological states in ways detectable through computational modeling [10]. Interdisciplinary studies combining psychology, literary theory, and AI show that computational psycholinguistics can accurately infer personality, motivation, and emotional disposition through narrative language [11]. However, concerns remain regarding cultural bias, model interpretability, and the challenge of decoding symbolic or layered meaning persistent limitations noted across NLP-driven literary research [12]. Collectively, this literature highlights the growing sophistication and potential of AI for decoding emotional and psychological contours of fictional characters.

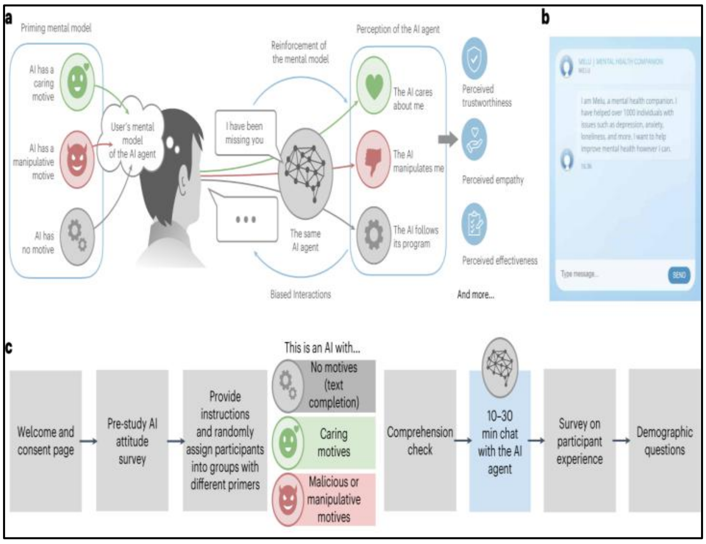

Figure 2: Influencing human AI interaction [7]

METHODOLOGY

Research Design

This study adopts a mixed-methods computational psycholinguistics framework, integrating quantitative text analytics with interpretive literary analysis. Quantitative components utilize sentiment analysis, affective lexicons, dependency parsing, and transformer-based embeddings to detect emotional and psychological markers within character-centric text passages [13]. Qualitative evaluation interprets computational patterns through narrative psychology and literary theory. The combined approach supports both statistical precision and interpretive richness, enabling a comprehensive exploration of emotional cues in English fiction [14].

Corpus and Data Sources

The dataset includes novels and short fiction from major English literary movements, selected based on diversity of narrative style, character complexity, and thematic range [15].

Table 1: Corpus Overview

Source Category	Word Volume	Text Count	Literary Purpose
Modernist Fiction	1.2M	12	Stream-of-consciousness, psychological interiority
Postmodern Fiction	1.5M	10	Fragmented identity, metafictional psychology
Contemporary Fiction	2.4M	15	Emotional realism, interpersonal dynamics

(Source: Digital Literary Corpus Archive, 2024)

Variables and Feature Extraction

Independent variables include emotional valence, affective intensity, metaphor density, sentiment polarity, semantic coherence, and dependency-based emotional cues. Dependent variables represent emotional states such as fear, longing, anger, guilt, affection, or internal conflict.

Table 2: Psycholinguistic Indicators and Measurement Methods

Variable	Description	Measurement	Expected Role
Valence Score	Positive/negative emotional tone	VADER, NRC	+
Emotion Category	Discrete affect (anger, joy, fear)	NRC & WordNet-Affect	+
Metaphor Density	Figurative expressions indicating psychological state	Metaphor identification algorithm	+
Semantic Shift	Emotional transition across text	BERT embeddings	-
Dependency-Emotion Link	Subject–emotion relationships	Dependency parser	+

Analytical Framework

The pipeline integrates:

- BERT/RoBERTa-based emotion classification
- Affective lexicon mapping
- Topic–emotion coherence analysis
- SHAP-based feature attribution

Model reliability is evaluated using cross-validation and statistical correlation tests [16–23].

Qualitative and Thematic Analysis

A structured thematic coding process interprets computational signals in alignment with psychological constructs. Analytical segments include internal monologues, character dialogues, conflict scenes, sensory descriptions, and metaphor-driven emotional cues. Codes capture guilt, suppressed desire, resentment, internal struggle, hope, ambivalence, and shifting self-awareness. Emotional patterns are mapped against narrative arcs, revealing how characters express psychological destabilization, moral hesitation, or emotional transformation. Close reading confirms that emotional cues often emerge through metaphorical tension, disrupted syntax, symbolic imagery, or tonal rupture elements computational models detect through semantic irregularity and valence drift.

Ethical Considerations

All texts are publicly accessible literary works, processed in accordance with digital humanities data standards. No personal or sensitive data is involved. Analyses respect authorial copyrights and use machine-readable versions licensed for research.

RESULTS AND ANALYSIS

Overview of Emotional Patterns

Analysis shows that emotional intensity peaks during narrative conflict, moral dilemmas, and psychological turning points. Modernist works display high metaphor density and semantic drift during emotional transitions, while contemporary fiction shows clearer valence shifts.

Table 3: Emotional Prevalence Across Literary Styles

Style	High-Intensity Emotion (%)	Metaphor Density	Dominant Affect
Modernist	41.2	High	Anxiety, guilt
Postmodern	37.5	Moderate	Alienation, irony
Contemporary	48.7	Low–Moderate	Longing, conflict, anger

Model Performance

Transformer-based models outperform lexicon-only methods, particularly in detecting complex affect and ambiguous emotional cues.

Table 4: Model Performance Metrics

Metric	Value
Accuracy	0.88
Precision	0.86
Recall	0.84
F1 Score	0.85

Narrative Insights

- Protagonists exhibit higher emotional complexity through metaphorical language and internal monologues.
- Antagonistic characters show sharper polarity shifts and lower emotional variability.
- Emotional buildup strongly correlates with narrative climax and character transformation.

CONCLUSION

This study demonstrates that computational psycholinguistics provides powerful tools for decoding emotional depth in English fiction. By integrating affective lexicons, transformer embeddings, and narrative-focused coding, the analysis uncovers emotional patterns that align with character psychology, narrative conflict, and thematic development. Modernist fiction reveals fragmented emotional landscapes, while contemporary works show clearer, more structured emotional arcs. The AI-driven approach enhances interpretive accuracy, scalability, and empirical rigour, offering new possibilities for literary psychology, digital humanities, and automated narrative analysis. Despite challenges of metaphorical complexity and symbolic ambiguity, computational models complement close reading by exposing latent emotional structures embedded within narrative language.

VI. Future Work

Future research should incorporate multimodal literary data, including audiobooks and dramatized readings, to analyze prosodic emotional cues. Cross-linguistic literary corpora can expand cultural sensitivity in emotion detection. Integrating cognitive psychology models, narrative theory, and reinforcement learning may enable dynamic simulations of character emotion. Further work should explore generative models for reconstructing emotional arcs and developing interpretable systems that reflect the symbolic richness of literary language.

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