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A Hybrid AI and Computational Linguistics Framework for Thematic and Narrative Analysis in Literary Studies

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***Abstract*—**This study examines the integration of artificial intelligence (AI) and computational linguistics as a hybrid methodological framework for thematic and narrative analysis in literary studies within the context of digital humanities. Addressing the limitations of traditional manual approaches, such as subjectivity and inefficiency in large-scale text analysis, this research employs a quantitative design involving 100 academics and educators. Data were analysed using the Wilcoxon signed-rank test and the Friedman test. The results indicate that narrative analysis received the highest level of appreciation, and statistical testing confirms that AI significantly enhances it. At the same time, computational linguistics contributes considerably to both the thematic and narrative domains. These findings demonstrate that hybrid computational approaches improve analytical efficiency, objectivity, and methodological consistency without eliminating the need for human interpretation. This study contributes a validated interdisciplinary framework that bridges computer science and literary studies, offering practical implications for education, content analysis, and digital humanities research.

***Keywords*—**Artificial Intelligence, Computational Linguistics, Thematic Analysis, Narrative Analysis

I. Introduction

The development of digital technologies has brought significant methodological changes to literary studies. One of the central challenges in contemporary literary research is conducting systematic thematic and narrative analysis on increasingly large and complex text corpora. Manual approaches remain widely used; however, they are time-consuming, susceptible to interpretive bias, and less effective when applied to large-scale datasets. This situation underscores the need for new methods that can process data more efficiently while maintaining interpretive consistency, as highlighted by recent developments in the digital humanities. (Joyeux-Prunel, 2024).

The integration of artificial intelligence (AI) and computational linguistics offers substantial potential to address these challenges. Natural language processing (NLP), as a significant branch of AI, has demonstrated strong capabilities in identifying thematic patterns, modelling narrative structures, and capturing semantic relations within literary texts with high precision. (Berhe et al., 2022; Bode, 2023).Meanwhile, computational linguistics provides the theoretical and algorithmic foundations necessary for analysing linguistic structures and meaning, including syntax, semantics, pragmatics, and discourse. (Altameemi & Altamimi, 2023; Jacobs, 2018).

Recent scholarship shows that computational approaches not only enhance analytical efficiency but also enable the discovery of latent patterns that may remain undetected through conventional close reading. O'Sullivan (2025) demonstrate that deep learning models can reveal thematic and stylistic tendencies that are not readily apparent to the human eye. Similarly, Sobchuk & Šeļa (2024) show that corpus-based semantic clustering provides more systematic insights into narrative patterns within literary texts.

Nevertheless, conceptual limitations remain. Figurative language, irony, metaphor, and cultural nuance often escape complete computational modelling. For this reason, integrating computational analysis with humanistic interpretation remains essential to ensure a comprehensive, contextually grounded understanding. (Banou et al., 2025; Chakrabarty et al., 2022).

Against this backdrop, the present study explores the integration of AI and computational linguistics as a hybrid methodological approach to strengthen thematic and narrative analysis in literary works. This approach is expected to advance methodological research in digital literary studies and enrich data-driven analytical practices in the modern era.

The development of digital technology has brought about significant transformation across various disciplines, including literary studies. One of the principal challenges in this field is to conduct systematic thematic and narrative analyses of large, diverse literary corpora. Traditionally, such processes have relied on manual approaches that require high precision, considerable time, and are often subject to the interpreter's subjectivity. These limitations render literary analysis less efficient and consistent, particularly in the face of the ever-expanding volume of texts in the digital era.

In this context, the integration of Artificial Intelligence (AI) and Computational Linguistics has emerged as a more effective and efficient methodological alternative. Natural Language Processing (NLP), a subfield of AI concerned with the interaction between computers and human language, has demonstrated considerable capability in tasks such as theme extraction, narrative pattern identification, and sentiment analysis within texts. Piper et al. (2021) Computational linguistics further contributes by providing the theoretical and algorithmic foundations for understanding the structure, meaning, and context of natural language, including within literary texts. (Jacobs, 2021).

Recent studies indicate that the application of AI in literary analysis is not merely a technical endeavour, but also requires consideration of epistemological and hermeneutic dimensions. For instance, research by Rybicki and Heydel illustrates how deep learning models can uncover hidden thematic patterns in Eastern European novels. (Rybicki & Heydel, 2021), whilst Ganascia highlights the importance of integrating computational linguistic methods with narratological theory in the field of digital humanities (Naseri & Momtazi, 2023).

Nevertheless, challenges such as the complexity of literary language, semantic ambiguity, and the use of cultural metaphors suggest that integrating AI and computational linguistics into literary studies still requires further development. There is an urgent need for conceptual and methodological frameworks that prioritise not only technical accuracy but also the validity of literary interpretation itself. (Banou et al., 2025).

Against this background, this article examines in depth how artificial intelligence and computational linguistics can be integrated into thematic and narrative analyses of literary works. The primary focus is on identifying conceptual frameworks, relevant methodologies, and the challenges and opportunities that arise in their application. It is expected that this article will contribute to interdisciplinary development between computer science and the humanities, particularly in digital humanities and literary studies, whilst offering alternative approaches that are more objective and systematic in the analysis of literary texts.

Despite the growing body of research on AI-assisted literary analysis, existing studies often focus on either artificial intelligence techniques or computational linguistics in isolation. Few studies have systematically integrated both approaches within a single analytical framework while simultaneously validating their effectiveness through empirical statistical testing. This gap limits the methodological robustness and interpretive reliability of computational literary studies.

This study advances the field by proposing and empirically validating a hybrid methodology that integrates AI-based models with computational linguistic analysis for thematic and narrative interpretation. By combining quantitative statistical validation with computational text analysis, this research contributes a novel, interdisciplinary framework that overcomes the limitations of purely manual or purely automated approaches in literary studies.

II. Literature Review

Thematic and narrative analysis have long been recognised as two central pillars in literary studies, both aiming to illuminate the meaning and structure of texts. Thematic analysis focuses on identifying patterns of ideas, motifs, and moral messages that constitute the core of a literary work. In contrast, narrative analysis focuses on plot, characters, conflict, and the author’s point of view. Abbott (2021)stresses that narrative is not merely a sequence of events but rather a cognitive construction that draws the reader into a fictional world with its own distinctive structure. Reinforces this view by emphasising that narrative analysis requires mapping the sequence of events as well as the relationships between narrative elements (Bal, 2017). However, manual methods traditionally employed in literary studies present notable limitations, particularly regarding the subjectivity of the interpreter and inefficiency when dealing with large textual corpora. Argue that such challenges have prompted the need for new approaches capable of processing texts more systematically and with technological support. (Underwood, 2019).

The development of artificial intelligence, particularly in the field of Natural Language Processing (NLP), has opened new opportunities for literary studies, in parallel with the expansion of digital humanities. Transformer-based deep learning models such as BERT, RoBERTa, and GPT have demonstrated a strong capacity to capture complex semantic contexts and inter-sentential relations in textual data. Through self-attention mechanisms, these models encode long-range dependencies and contextual meaning across sentences, enabling nuanced representations of narrative coherence, thematic continuity, and stylistic variation. (Devlin et al., 2019; Liu et al., 2020). Techniques already in use include topic modelling, narrative event extraction, and story graph generation. Propose a neural topic modelling approach specifically designed to support humanities research. Similarly, Murdock illustrates how explainable AI may be applied to generate literary analyses that are not only accurate but also academically interpretable. (Murdock et al., 2022). AI, therefore, functions not merely as a technical tool but also as a methodological instrument reshaping data-driven paradigms of literary interpretation.

In parallel, computational linguistics serves as both a theoretical and methodological foundation in the development of AI systems for literary text analysis. Define computational linguistics as an interdisciplinary field that integrates linguistics, computer science, and mathematics to understand and process human language (Jurafsky & Martin, 2023). In literary studies, computational linguistics enables more in-depth analyses of the lexical, syntactic, semantic, and pragmatic aspects of texts. Jacobs and Dunst highlight techniques such as corpus linguistics, semantic role labelling, and narrative schema modelling as central to linguistic analyses of literature(Dunst et al., 2022). Stress the importance of using large, representative corpora to ensure findings that are both valid and generalisable. Furthermore, Gildea, Jurafsky, and Rashkin developed methods for identifying semantic roles in narrative, thus supporting the analysis of characters and actions within stories (Bal, 2017).

The integration of artificial intelligence and computational linguistics in literary analysis has given rise to an interdisciplinary approach known as computational literary studies. Hatzel et al. (2023)argue that machine learning in computational literary studies functions most productively when embedded within interpretive workflows, thereby enabling a synthesis between automated text processing and humanistic literary analysis. Shows that such integration can uncover thematic and narrative patterns that would otherwise remain inaccessible through manual methods Naseri & Momtazi (2023) For instance, Rybicki & Heydel (2021) employed deep learning to detect hidden thematic structures in Eastern European novels, whilst Ganascia advanced a framework that integrates computational linguistics with narratological theory within digital humanities. Nonetheless, challenges remain, particularly regarding AI's limited capacity to comprehend metaphor, irony, and the cultural contexts embedded in literary texts. Affirm that although AI models have progressed significantly, the interpretation of figurative language and cultural values still necessitates active involvement from humanities scholars. (Jacobs, 2021; Naseri & Momtazi, 2023).

Accordingly, the theoretical framework of this article positions the integration of artificial intelligence and computational linguistics as an interdisciplinary endeavour that combines data-driven quantitative methods with theory-informed qualitative interpretation. This approach does not seek to replace traditional humanistic methodologies but rather to expand the scope and depth of analysis, whilst simultaneously opening new avenues for technologically enhanced literary studies.

This research adopts an exploratory qualitative approach, supported by computational linguistics and AI-based methods, specifically within the framework of computational literary analysis. This design was chosen to systematically examine the integration of AI and computational linguistics in the thematic and narrative analysis of literary works, whilst also constructing an analytical model applicable to bilingual corpora, namely Indonesian and English.

The objects of study comprise a corpus of modern prose fiction, including works awarded the Kusala Sastra Khatulistiwa and published in 2025. The texts were purposively selected based on the following criteria: they must possess a coherent narrative structure, represent both popular and literary fiction genres, and be available in digital formats amenable to automatic processing. Data sources include the National Digital Library, digital publishing platforms, Project Gutenberg, HathiTrust, and Open Library.

Data collection was conducted in two main stages: text extraction and preprocessing. Text extraction involved converting digital files to machine-readable formats using Python and libraries such as BeautifulSoup and PyPDF2. The preprocessing stage sought to remove non-narrative elements irrelevant to analysis, such as chapter titles, footnotes, or metadata. This included tokenisation, stopword removal, lemmatisation, and named-entity recognition filtering, implemented using NLP libraries such as NLTK, spaCy, and Stanza.

The data analysis techniques employed consist of three interrelated stages. The first stage is thematic analysis using topic modelling, implemented through Latent Dirichlet Allocation (LDA) and BERTopic. This process was executed in Python using the Gensim and BERTopic libraries, and the results were evaluated using coherence scores and validated by human expert panels to ensure interpretative accuracy in literary contexts.

The second stage is narrative analysis conducted via narrative event extraction, employing deep learning transformer-based models such as Event2Mind and Narrative Arc Detection. Tools, including AllenNLP and Huggingface Transformers, were utilised to extract narrative elements such as event sequences, character relations, and plot construction. The outputs consisted of narrative arc graphs and character-event relation mappings, visualised in Gephi.

The third stage integrates the results of the thematic and narrative analyses, presenting them as story graphs and interactive dashboards using pyLDAvis and Gephi. To ensure data validity, methodological triangulation was conducted by comparing LDA and BERTopic outputs, cross-corpus triangulation between Indonesian and English texts, and expert review through focus group discussions (FGDs) involving five scholars in literary studies and computational linguistics.

Model performance evaluation used perplexity for topic modelling and F1 Scores for narrative event extraction. All data collection and processing adhered to principles of research ethics, particularly regarding licensing of digital literary works and respect for copyright. The texts utilised in this study were either in the public domain or distributed with proper copyright permissions.

Within this methodological framework, the research seeks to develop an analytical model that is not only technically valid but also theoretically and practically relevant to advancing technologically enhanced literary studies within the digital humanities.

Recent studies in digital humanities increasingly highlight the need for hybrid methodologies that combine computational efficiency with interpretive validity. (Bode & Bradley, 2025; Dobson, 2019). However, many of these studies end with conceptual discussions, without empirical validation, particularly through statistical testing with expert users. This study addresses this limitation by empirically evaluating the perceived effectiveness of AI and computational linguistics in literary analysis.

III. METHODS

In this study, artificial intelligence tools were employed not as autonomous interpreters, but as analytical instruments designed to assist human interpretation. AI models were used to identify thematic clusters and narrative structures based on statistical and linguistic patterns, while final interpretation and validation were conducted through expert review. This human-in-the-loop approach ensures that computational outputs remain aligned with literary and cultural contexts.

To clarify the structure and sequence of the research methodology, the overall research framework is illustrated in Figure 1. The figure presents a schematic representation of the research process, from data collection through hypothesis testing to conclusion drawing.

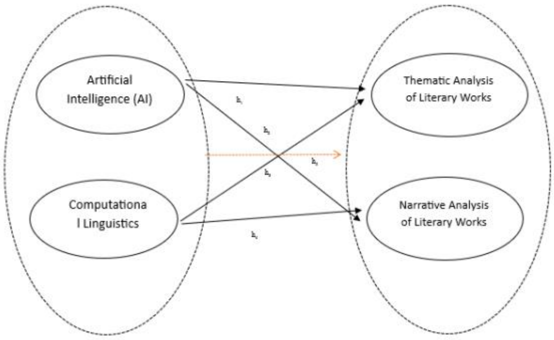

Figure 1. Research Framework

This study adopts a quantitative research approach. Data were collected using a closed-ended questionnaire, in which respondents were required to select responses. Involved educators, both teachers and lecturers from several higher education institutions, and the analysis was conducted using the JASP application.

The results of the validity testing for the Artificial Intelligence (AI) variable are summarized in Table 1, which presents the number of items and the number of valid items for each indicator and negative statements: Strongly Agree (SA), Agree (A), Neutral, Disagree (D), and Strongly Disagree (SD). Before the main data collection, the research instrument underwent validity and reliability testing, including a pilot test using predefined options. Five Likert-scale response categories were provided, including both positive and negative options.

Table 1. Validity Test Results of the Artificial Intelligence (AI) Variable

Variable	Indicator	Number of Items	Number of Valid items
Artificial Intelligence (AI)	Knowledge Representation	15	15
	Logical Reasoning and Inference		
	Machine Learning		
	Natural Language Processing (NLP)		
Total items			15

100 respondents completed 15 statement items. An item was considered valid if the p-value was less than 0.05. The detailed results of the JASP validity analysis for the AI variable are further illustrated in Figure 2.

Correlation

Pearson Correlation ▾

Variable	Column 1	Column 2	Column 3	Column 4	Column 3	Column 6	Column 7	Column 8	Column 10	Column 11	Column 12	Column 13	Column	Total
	Sig. (p-value)	—	—	—	—	—	—	—	—	—	—	—	—	—
1. Column 1	—	—	—	—	—	—	—	—	—	—	—	—	—	
Pearson r	0,641	0,641	—	—	—	—	—	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001												
2. Column 2	0,620	0,565	0,685	—	—	—	—	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001											
3. Column 3	0,655	0,669	0,681	0,665	—	—	—	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001										
4. Column 4	0,655	0,699	0,655	0,633	0,771	—	—	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001									
5. Column 5	0,663	0,669	0,681	0,693	0,695	0,771	—	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001								
6. Column 6	0,653	0,683	0,685	0,665	0,374	0,563	0,771	—	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001							
7. Column 7	0,659	0,668	0,681	0,693	0,665	0,665	0,703	0.745	—	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001						
8. Column 6	0,684	0,761	0,696	0,663	0,693	0,686	0,685	0,693	0,731	—	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001					
9. Column 10	0,626	0,687	0,605	0,696	0,685	0,633	0,765	0.705	0,695	0,749	—	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001				
10. Column 11	0,657	0,621	0,606	0,663	0,665	0,705	0,793	0.705	0,695	0,685	0,723	—	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001			
11. Column 12	0,637	0,609	0,699	0,662	0,665	0,693	0,695	0,695	0,695	0,695	0,695	0,789	—	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		
12. Column 13	0,694	0,465	0,673	0,606	0,874	0,695	0,697	0,695	0,695	0,693	0,695	0,695	0,695	
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
13. Column 14	0,653	0,956	0.400	0,667	0,683	0,695	0,696	0.705	0,695	0,695	0,695	0,685	0,685	—
Sig. (p¬)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
14. **Total**	0,657	0,656	0,697	0,667	0,695	0,666	0,696	0,693	0,696	0,693	0,695	0,695		228

Figure 2. Result of the Validity Test for the Computational Linguistics Variable

As shown in Figure 2, all 15 items are declared valid, as each item yielded a p-value below 0.05 among the 100 respondents.

The validity test results for the Computational Linguistics variable are presented in Table 2, which summarizes the indicators, total items, and valid items.

Table 2. Results of the Validity Test for the Computational Linguistics Variable

Variable	Indicator	Number of Items	Number of Valid items
Computational Linguistics	Representation and Processing of Phonetics & Phonology	15	15
	Computational Morphology		
	Syntactic Parsing & Formal Grammar		
	Semantic Representation		
Total items			15

All 15 statement items completed by 100 respondents meet the validity criterion (p-value < 0.05).

Table 3. Validity Test Results for the Variable of Thematic Analysis of Literary Works

Variable	Indicator	Number of Items	Number of Valid items
Thematic Analysis of Literary Works	Identification of subjects and themes	16	16
	Methods of formulating thematic statements		
	Exploration through characters and conflicts		
	Thematic markers: symbols, motifs, and utterances		
Total items			16

100 respondents completed 16 statement items. An item is considered valid if the *p*-value is less than 0.05. The following presents the JASP validity test results for the variable of thematic analysis of literary works:

Correlation

Pearsor Correlation

Variable	Pearson / Sig. (p-value)	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7	Column 8	Column 10	Column 12	Column 17	
1. Column 1	—	—	—	—	—	—	—	—	—	—	—	—	
Pearson r	0,701	0,701	0,701	—	—	—	—	—	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001										
2. Column 2	0,620	0,630	0,681	0,655	—	—	—	—	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001									
3. Column 3	0,655	0,699	0,681	0,663	0,771	—	—	—	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001								
4. Column 4	0,655	0,653	0,609	0,665	0,653	0,771	—	—	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001							
5. Column 5	0,653	0,699	0,681	0,663	0,663	0,695	0,731	—	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001						
6. Column 6	0,653	0,696	0,298	0,665	0,374	0,595	0,753	0,745	—	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001					
7. Column 7	0,653	0,663	0,699	0,666	0,666	0,699	0,685	0,749	0,745	—	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001				
8. Column 8	0,637	0,653	0,291	0,665	0,673	0,395	0,703	0,705	0,693	0,692	—	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001			
9. Column 9	0,626	0,667	0,606	0,663	0,653	0,699	0,635	0,695	0,695	0,635	0,749	—	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		
10. Column 10	0,657	0,731	0,777	0,693	0,647	0,595	0,705	0,704	0,705	0,793	0,705	0,723	
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
11. Column 11	0,637	0,699	0,609	0,666	0,683	0,699	0,693	0,896	0,696	0,695	0,699	0,895	—
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
12. Column 12	0,653	0,420	0,773	0,693	0,664	0,665	0,707	0,707	0,697	0,695	0,693	0,921	—
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
17. Column 17	0,932	0,400	0,400	0,699	0,696	0,695	0,898	0,898	0,693	0,695	0,899	0,804	—
Sig. (p↖)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	

Figure 3. Validity Test Results for Thematic Analysis of Literary Works

As shown in Figure 3, all 16 items are declared valid, as the p-values for all items are less than 0.05.

Table 4. Validity Test Results for Thematic Analysis of Literary Works

Variable	Indicator	Number of Items	Number of Valid items
Thematic Analysis of Literary Works	Identification of subjects and themes	16	16
	Methods of formulating thematic statements		
	Exploration through characters and conflicts		
	Thematic markers: symbols, motifs, and utterances		
Total items			16

All 16 items are declared valid, as their p-values are less than 0.05. The detailed results of the JASP validity analysis for this variable are illustrated in Figure 4.

Correlation

Reports Correlations

Variable	Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 10	Column 11	Column 12	Column 13	Column 14	Column 17
1. Column 1	—	—	—	—	—	—	—	—	—	—	—	—
2. Column 2	0.701	—										
Sig. (2-tailed)	< .001	< .001	—									
3. Column 3	0.833	0.678	0.706	—								
Sig. (2-tailed)	< .001	< .001	< .001	< .001	—							
4. Column 4	0.579	0.608	0.723	0.706	0.706	—						
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	—					
5. Column 5	0.439	0.567	0.493	0.660	0.563	0.667	0.721	—				
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—			
6. Column 6	0.540	0.364	0.582	0.683	0.698	0.684	0.843	0.632	0.729	—		
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001		
7. Column 7	0.899	0.493	0.599	0.693	0.649	0.807	0.895	0.899	0.839	0.832	—	
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	—
8. Column 8	0.596	0.468	0.553	0.898	0.698	0.893	0.899	0.895	0.867	0.723	0.722	0.871
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
9. Column 9	0.460	0.628	0.564	0.693	0.684	0.663	0.852	0.669	0.872	0.697	0.746	0.629
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
10. Column 10	0.559	0.648	0.665	0.696	0.641	0.694	0.856	0.863	0.866	0.800	0.723	0.699
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
11. Column 11	0.558	0.562	0.568	0.693	0.681	0.669	0.699	0.693	0.733	0.787	0.728	0.657
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
12. Column 12	0.669	0.469	0.668	0.686	0.666	0.686	0.686	0.684	0.668	0.683	0.728	0.698
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
13. Column 11	0.595	0.538	0.568	0.664	0.641	0.666	0.666	0.688	0.929	0.853	0.721	0.698
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
17. Column 17	0.800	0.808	0.664	0.689	0.664	0.689	0.684	0.669	0.668	0.734	0.800	0.800
Sig. (2-tailed)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001 —

Figure 4. Results of the Validity Test for Narrative Analysis of Literary Works

It can be inferred that all 16 items are valid, as the p-value is less than 0.05 with 100 respondents.

The reliability test was conducted using the JASP application, with the assessment criterion stating that if the estimated coefficient α ≥ 0.7, the instrument is considered reliable; otherwise, it is deemed unreliable. The results of the reliability test are presented in the following table:

Table 5. Reliability Test Results for the Artificial Intelligence (AI) Variable

Statistic	Value
Cronbach's Alpha (α)	0.942
Standard Error	0.018
95% CI (Lower)	0.907
95% CI (Upper)	0.977

Based on Table 5, the instrument demonstrates high reliability, with an estimated Cronbach's alpha of 0.942, exceeding the minimum reliability threshold of 0.7.

Table 6. Reliability Test Results for the Computational Linguistics Variable

Statistic	Value
Cronbach's Alpha (α)	0.954
Standard Error	0.012
95% CI (Lower)	0.931
95% CI (Upper)	0.978

As shown in Table 6, the estimated coefficient α of 0.954 indicates that the instrument for the Computational Linguistics variable is reliable.

Furthermore, the reliability testing results for the thematic literary analysis variable are summarized in Table 7.

Table 7. Reliability Test Results for the Thematic Literary Analysis Variable

Statistic	Value
Cronbach's Alpha (α)	0.955
Standard Error	0.012
95% CI (Lower)	0.931
95% CI (Upper)	0.979

Based on Table 7, the thematic literary analysis instrument is confirmed to be reliable, with a Cronbach's alpha coefficient of 0.955.

Similarly, the reliability results for the narrative literary analysis variable are presented in Table 8.

Table 8. Reliability Test Results for the Narrative Literary Analysis Variable

Statistic	Value
Cronbach's Alpha (α)	0.950
Standard Error	0.014
95% CI (Lower)	0.922
95% CI (Upper)	0.978

As indicated in Table 8, the narrative literary analysis instrument meets the reliability criterion, with an estimated alpha coefficient of 0.950.

After the reliability testing phase, the research proceeded to the results testing stage. Data were collected from teachers and lecturers using a purposive sampling technique. Once the data were obtained, hypothesis testing was conducted using the t-test to examine relationships among variables for artificial intelligence, computational linguistics, thematic literary analysis, and narrative literary analysis. The hypotheses tested in this study are as follows:

H01: There is no significant difference between the artificial intelligence variable and thematic literary analysis.

Ha1: There is a significant difference between the artificial intelligence variable and the thematic literary analysis.

H02: There is no significant difference between the artificial intelligence variable and narrative literary analysis.

Ha2: There is a significant difference between the artificial intelligence variable and the narrative literary analysis.

H03: There is no significant difference between the computational linguistics variable and thematic literary analysis.

Ha3: There is a significant difference between the computational linguistics variable and the thematic literary analysis.

H04: There is no significant difference between the computational linguistics variable and narrative literary analysis.

Ha4: There is a significant difference between the computational linguistics variable and narrative literary analysis.

H05: There is no significant joint difference between artificial intelligence and computational linguistics variables on thematic literary analysis and narrative literary analysis.

Ha5: There is a significant joint difference between artificial intelligence and computational linguistics variables on thematic literary analysis and narrative literary analysis.

The decision rule for hypothesis testing was based on the p-value criterion: if the p-value ≤ 0.05, the null hypothesis (H_0) is rejected; otherwise, it is accepted. Upon completing the hypothesis testing, the final stage of the research involved drawing conclusions from the statistical findings.

IV. Result And Discussion

A. Result

To conduct the statistical analysis, the researcher employed SPSS version 26. This study applied a nonparametric test to determine whether there are significant differences across the variables, both partially and simultaneously. The results of the statistical analysis are presented as follows:

1. Descriptive Statistical Analysis

Table 9. Descriptive Statistical Analysis Results

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Artificial Intelligence (AI)	100	15	60	45.88	6.036
Computational Linguistics	100	15	60	44.12	6.896
Thematic Analysis	100	15	60	47.22	6.840
Narrative Analysis	100	15	60	48.32	6.772

Based on the descriptive statistical analysis, this study involved 100 respondents and four principal variables: Artificial Intelligence (AI), Computational Linguistics, Thematic Analysis, and Narrative Analysis. The results indicate that the highest mean score was recorded for the Narrative Analysis variable, at 48.32 with a standard deviation of 6.772, followed by Thematic Analysis, with a mean of 47.22 and a standard deviation of 6.840. Meanwhile, the AI variable obtained a mean score of 45.88 (SD = 6.036), and Computational Linguistics recorded the lowest mean at 44.12 (SD = 6.896). This suggests that respondents demonstrated a stronger inclination towards the narrative analysis approach compared with the other variables

2. Wilcoxon Test between AI and Thematic Analysis of Literary Works

Table 10. Results of the Wilcoxon Test between the AI Variable and Thematic Analysis of Literary Works

Comparison	Z	p-value (2-tailed)	Decision
Thematic Analysis – AI	-1.554	0.120	Not Significant

The comparison between AI and Thematic Analysis of Literary Works yielded a Z score of –1.554 ($p = 0.120$), indicating no significant difference between the two variables. Accordingly, the first hypothesis test accepts H01 and rejects Ha1.

3. Wilcoxon Test of the AI Variable with Narrative Analysis of Literary Works

Table 11. Results of the Wilcoxon Test for the AI Variable with Narrative Analysis of Literary Works

Comparison	Z	p-value (2-tailed)	Decision
Narrative Analysis – AI	-3.020	0.003	Significant

The comparison between AI and Narrative Analysis of Literary Works yielded a Z value of -3.020 with a significance level of 0.003 (< 0.05), indicating a significant difference between the two variables. Accordingly, the second hypothesis test accepts Ha2 and rejects H02.

4. Wilcoxon Test of the Computational Linguistics Variable with Thematic Analysis of Literary Works

Table 12. Results of the Wilcoxon Test for the Computational Linguistics Variable with Thematic Analysis of Literary Works

Comparison	Z	p-value (2-tailed)	Decision
Thematic Analysis – Computational Linguistics	-3.100	0.002	Significant

The comparison between Computational Linguistics and Thematic Analysis yielded a Z value of -3.100 with a significance level of 0.002 (< 0.05), indicating a significant difference. Accordingly, the third hypothesis test accepts Ha3 and rejects H03.

5. Wilcoxon Test of Computational Linguistics with Narrative Analysis of Literary Works

Table 13. Results of the Wilcoxon Test for Computational Linguistics and Narrative Analysis of Literary Works

Comparison	Z	p-value (2-tailed)	Decision
Narrative Analysis – Computational Linguistics	-4.609	< 0.001	Significant

The comparison between Computational Linguistics and Narrative Analysis yielded a Z value of -4.609, with a p-value of 0.000 (< 0.05), indicating a significant difference. Accordingly, the fourth hypothesis test accepts Ha4 and rejects H04

6. Friedman Test

Table 14. Results of the Friedman Test Analysis

Statistic	Value
N	100
Chi-Square (χ^2)	33.924
Degrees of Freedom	3
Asymp. Sig.	< 0.001

Based on Table 14, the Chi-Square value is 33.924 with 3 degrees of freedom (df) and a significance level (Asymp. Sig.) of 0.000 (< 0.05). This indicates a significant difference among the four variables tested. Accordingly, the fifth hypothesis test accepts Ha5 and rejects H05.

B. Discussion

Based on the data presented above, the findings indicate that integrating Artificial Intelligence (AI) and Computational Linguistics is highly relevant for supporting both thematic and narrative analyses of literary works. The descriptive results show that the Narrative Analysis variable obtained the highest mean score (M = 48.32), followed by Thematic Analysis (M = 47.22), AI (M = 45.88), and Computational Linguistics (M = 44.12). Overall, this suggests that respondents tended to appreciate the narrative-based approach more than the thematic approach, while recognising AI and Computational Linguistics as relevant methodological tools, albeit not yet thoroughly dominant. These findings align with Abbott (2021), who argues that narratives constitute cognitive constructs that are more readily internalised by readers than mere theme identification, as they involve dimensions of experience, conflict, and character dynamics.

The Wilcoxon test between AI and Thematic Analysis yielded a p-value of 0.120 (> 0.05), indicating no significant difference between the two. In other words, AI can provide support comparable to traditional thematic analysis approaches. This finding reinforces the view that AI, through distant reading and topic modelling, can replicate the achievements of conventional thematic analysis at scale. Nonetheless, the absence of a significant difference also suggests that AI has not produced a methodological leap in this context, but rather functions as an alternative that enhances efficiency and objectivity.

Conversely, the Wilcoxon test between AI and Narrative Analysis yielded a significance value of 0.003 (< 0.05), indicating a significant difference. This demonstrates that AI plays a more substantial role in supporting narrative analysis than traditional methods alone. These results align with the studies. (Chaturvedi et al., 2017; Rashkin et al., 2018) who developed the Event2Mind model to predict events, intentions, and character reactions in narratives. Thus, AI not only assists in detecting storylines but also links character motivations to narrative development, a task that is challenging to achieve manually. This explains why significant differences emerge in the narrative aspect, as AI adds value in representing the complexity of character relationships and events.

Meanwhile, the Wilcoxon test between Computational Linguistics and Thematic Analysis showed a significance of 0.002 (< 0.05), indicating a significant difference. This demonstrates that the application of Computational Linguistics uniquely contributes to thematic analysis, particularly in semantic representation and the exploration of linguistic motifs. Emphasises that Computational Linguistics enables deeper reading of semantic structures, allowing themes to be identified not only from the surface narrative but also through lexical analysis and semantic role examination. These findings suggest that Computational Linguistics can enrich the theme identification process by providing a stronger linguistic foundation compared to manual methods. (OMAR, 2021).

Furthermore, the Wilcoxon test between Computational Linguistics and Narrative Analysis showed a p-value of 0.000 (< 0.05), indicating a significant difference. This underscores the role of Computational Linguistics in elucidating narrative structures more thoroughly, for example, through character network mapping and syntactic relation analysis. Support this finding, showing that semantic role-based representations enable AI systems to identify interconnections among events within a story. Consequently, Computational Linguistics contributes significantly, in different ways, to narrative analysis, particularly in the formal linguistic aspects that shape the construction of the story.

The most critical findings of this study arise from the Friedman test, which yielded a Chi-Square value of 33.924 and a p-value of 0.000 (< 0.05). This confirms that there are significant differences among the four variables (AI, Computational Linguistics, Thematic Analysis, and Narrative Analysis). Collectively, AI and Computational Linguistics contribute meaningfully to the development of methodologies for literary analysis. This supports those who argue that computational literary studies open new avenues for interaction between computer science and the humanities, where AI and Computational Linguistics serve not merely as technical tools but also as a novel epistemological framework. (Bode & Bradley, 2024).

Further discussion can focus on epistemological and hermeneutic aspects. While AI and Computational Linguistics can support large-scale literary data analysis, challenges remain in dealing with figurative language, metaphors, and cultural contexts. As noted, AI systems are still prone to social biases and struggle to grasp contextual meaning fully. Therefore, although the present study demonstrates significant differences and meaningful contributions of AI and Computational Linguistics, traditional hermeneutic approaches remain relevant to ensure the validity of literary interpretation (Dobson, 2022).

The practical implication of these findings is that integrating AI and Computational Linguistics can help literary researchers manage large corpora more efficiently and objectively. However, AI cannot fully replace the depth of qualitative analysis rooted in the humanities. On the contrary, their integration provides a richer hybrid methodology. Emphasise that digital humanities is not an effort to replace human interpretation with machines, but a collaboration between the two to achieve a broader understanding (Underwood, 2019).

In conclusion, this study contributes to the understanding that Narrative Analysis receives the highest appreciation from respondents; AI provides significant support, particularly in the narrative domain; Computational Linguistics enriches both thematic and narrative analyses; and, collectively, these technologies demonstrate clear advantages over traditional methods. The findings underscore the urgency of integrating quantitative, technology-based methodologies with qualitative, theory-based approaches in literary studies, thus creating a more comprehensive and adaptive research ecosystem in the digital era.

1. Broader Implications for Education, Content Analysis, and Digital Humanities

The findings of this study have implications beyond literary studies, particularly for education, content analysis, and digital humanities. In educational contexts, integrating AI and computational linguistics can support literature instruction by enabling students and educators to explore themes and narrative structures more systematically, especially when working with large reading corpora. This approach may enhance critical reading skills by combining computational insights with interpretive discussion.

In the field of content analysis, the proposed hybrid methodology offers a scalable, replicable framework for analysing narrative-based materials, such as digital storytelling, historical documents, and media texts. By reducing subjectivity while maintaining interpretive depth, this approach addresses long-standing methodological tensions in qualitative research.

Within digital humanities, this study contributes to ongoing debates on how computational methods can coexist with hermeneutic traditions. Rather than replacing close reading, the integration of AI and computational linguistics extends analytical capacity, enabling scholars to identify large-scale narrative patterns while preserving contextual and cultural interpretation.

V. Conclusion

This study demonstrates that integrating Artificial Intelligence (AI) and Computational Linguistics significantly enhances both thematic and narrative analyses of literary works. The findings indicate that Narrative Analysis received the highest appreciation from respondents, followed by Thematic Analysis, while AI and Computational Linguistics were perceived as effective supporting instruments. The Wilcoxon tests confirm that AI plays a crucial role in supporting narrative analysis. In contrast, Computational Linguistics enriches both thematic and narrative analyses by providing greater semantic depth and more detailed linguistic mapping.

Simultaneously, the Friedman test results affirm significant differences among the four variables, indicating that AI and Computational Linguistics function not merely as technical tools but also as a novel methodological framework in digital literary studies. Consequently, their integration offers a more systematic, efficient, and objective hybrid approach, while still requiring hermeneutic interpretation to ensure the validity of literary meaning. This study underscores the importance of collaboration between technology and the humanities in developing a comprehensive and adaptive approach to scholarly research in the digital era.

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