Vol. 8 No. 1
June 2026
e- ISSN 2685 - 0559
p- ISSN 2684 - 673X
Published by Asosiasi Ide Bahasa Kepri
Jurnal Ide Bahasa
Inspirasi Dosen Bahasa dan Sastra

A MORPHOLOGICAL ANALYSIS OF AI-GENERATED ENGLISH TEXTS COMPARED TO HUMAN ACADEMIC WRITING

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ABSTRACT

This study investigated the morphological characteristics of AI-generated English texts in comparison with human academic writing, focusing on affixation, compounding, lexical patterns, and word-formation processes. It specifically aimed to identify morphological differences between both text types, examine how AI language models construct academic discourse at the word-formation level, and determine whether morphological analysis can effectively distinguish machine-produced from human-written academic texts. Ten academic texts — five ChatGPT-generated outputs and five drawn from student essays and final assignment articles — were purposively selected based on comparable topic, length, and register. Employing a qualitative descriptive design with a comparative approach, data were collected through documentation and analyzed using qualitative content analysis framework of data condensation, data display, and conclusion drawing. Morphological features were systematically classified into derivational affixes, inflectional affixes, compounds, acronyms, and lexical patterns. The findings revealed notable distinctions between the two text types. AI-generated texts displayed higher frequencies of derivational suffixes (186 instances) and lexical repetition (79 instances), with heavy dependence on standardized suffixes such as *-tion*, *-ment*, and *-ity* to sustain academic formality. Human-written texts, conversely, exhibited greater morphological complexity through multi-affix constructions like *misinterpretation* and *unpredictability*, richer compounding patterns including *self-regulated learning* and *cross-cultural communication*, and broader lexical diversity achieved through synonym substitution. The study concludes that, while AI-generated writing demonstrates grammatical consistency, human academic discourse remains superior in lexical richness, morphological creativity, and contextual adaptability.

Keywords: AI-generated writing, Human academic writing, Lexical variation, Morphological analysis, Word formation processes

1. Introduction

The rapid development of artificial intelligence has significantly influenced various areas of modern education, particularly academic writing. AI-based language models, especially OpenAI's ChatGPT, have become increasingly integrated into writing activities at undergraduate and postgraduate levels. These technologies enable users to produce coherent and grammatically accurate academic texts efficiently (Kasneci et al., 2023; Dwivedi et al., 2023). Although this advancement offers considerable benefits for students and researchers, it has also generated concerns regarding the authenticity, linguistic quality, and reliability of AI-generated academic texts. As AI writing tools continue to gain popularity in educational settings, it has become increasingly important to investigate how the linguistic features of AI-produced texts differ from those created by human writers (Zhai, 2022; Cotton et al., 2023).

One useful perspective for examining this distinction is morphology, the branch of linguistics that studies the internal structure of words and the processes through which they are formed. Morphological processes such as affixation, compounding, blending, and derivation contribute substantially to lexical sophistication, textual cohesion, and communicative effectiveness in academic writing (Lieber, 2016; Booij, 2019). A writer's morphological competence, reflected in the ability to use diverse derivational forms, discipline-specific compounds, and contextually appropriate vocabulary, is often considered an indicator of academic language proficiency (Goodwin & Ahn, 2019). Differences between AI-generated and human-written texts are likely to become apparent at the morphological level because AI systems generate language through statistical prediction rather than through genuine communicative understanding.

The data examined in this study consist of AI-generated texts produced by ChatGPT and authentic academic texts written by university students and academic authors. These sources were intentionally selected because they represent two highly relevant forms of academic writing in contemporary educational contexts. As one of the most widely used AI writing tools in higher education, ChatGPT serves as an appropriate example of machine-generated academic discourse (van Dis et al., 2023). In contrast, student essays and scholarly articles represent authentic academic writing shaped by individual cognition, disciplinary expertise, and communicative awareness (Hyland, 2019). The presence of both text types within current academic environments makes their morphological comparison both meaningful and theoretically justified.

Despite the growing number of studies on AI-generated writing, previous research has focused mainly on syntactic structure, semantic coherence, plagiarism issues, and ethical considerations, while morphological aspects have received relatively limited attention. Cotton et al. (2023) and Tlili et al. (2023) reported that AI-generated texts generally demonstrate high levels of grammatical accuracy and structural consistency; however, their studies did not examine word-formation patterns in detail. Similarly, Perkins (2023) observed that AI writing often relies on formulaic vocabulary and repetitive lexical choices, while Gao et al. (2023) highlighted its dependence on predictable sentence structures. Although these findings suggest potential morphological issues, they do not directly address them. Likewise, van Dis et al. (2023) discussed the linguistic limitations of AI-generated discourse but did not conduct a systematic comparison of its morphological features with those found in human academic writing. This gap in the literature provides the main rationale for the present study.

Therefore, this study aims to analyze and compare the morphological characteristics of AI-generated English texts and human academic writing by focusing on affixation, compounding, lexical patterns, and word-formation processes. Specifically, the research seeks to identify similarities and differences in morphological usage between the two text types, investigate how AI language models construct academic discourse at the morphological level, and evaluate the effectiveness of morphological analysis in distinguishing textual origins. The originality of this study lies in its emphasis on morphology as a primary analytical framework, an area that remains largely underexplored in research on AI-generated academic writing. By addressing this gap, the study contributes to a deeper linguistic understanding of both the capabilities and limitations of artificial intelligence in producing academic discourse.

2. LITERATURE REVIEW

Morphology is a major branch of linguistics that focuses on the structure, formation, and organization of words within a language. It examines how morphemes, which are the smallest units of meaning, combine and interact to create words that carry both lexical and grammatical information (Lieber, 2016; Yule, 2020). These processes follow specific linguistic rules that govern how words are formed, modified, and interpreted in different communicative situations. According to Booij (2019), morphological knowledge extends beyond describing word structures, as it also contributes significantly to vocabulary growth, language learning, and the development of communicative competence, particularly in academic and literacy-related contexts. Therefore, an understanding of morphology is essential for examining the structural characteristics of written texts and understanding how meaning is constructed through word formation.

Word formation in English consists of several systematic processes that allow speakers and writers to create new words or modify existing ones. Among the most common and productive processes are affixation, compounding, blending, clipping, and acronym formation, each of which contributes to the diversity and development of English vocabulary (Lieber, 2016; Bauer, 2003). Affixation involves attaching prefixes or suffixes to a root or base word in order to create a new form or modify its meaning. This process can be divided into derivational and inflectional affixation. Derivational affixes create new lexical items or change the grammatical category of a word, such as teacher from teach or unhappy from happy. In contrast, inflectional affixes express grammatical information such as tense, number, possession, or comparison without altering the word's basic meaning or word class, as seen in walked and books (Yule, 2020; Matthews, 2002). In academic writing, derivational affixation plays a particularly important role because suffixes such as -tion, -ity, -ment, and -ness frequently contribute to the formal and abstract style associated with scholarly communication (Booij, 2019).

Compounding is another important word-formation process in which two or more independent words are combined to create a new lexical item with a unified meaning, such as blackboard, decision-making, or knowledge-construction

(Bauer, 2003; Plag, 2018). Although compounds may appear as a single word, a hyphenated form, or separate words, they function as a single semantic unit. This process is especially common in academic and technical discourse, where compound expressions allow complex concepts to be expressed efficiently and precisely. Blending, on the other hand, involves combining parts of two existing words to form a new term, such as brunch from breakfast and lunch or edutainment from education and entertainment (Lieber, 2016; Yule, 2020). Clipping refers to shortening a longer word while retaining its original meaning, as illustrated by forms such as prof for professor and lab for laboratory (Matthews, 2002; Plag, 2018). In addition, acronym formation creates new lexical items from the initial letters of multi-word expressions, producing forms such as NLP for Natural Language Processing and AI for Artificial Intelligence, which are widely used in scientific and technical fields (Bauer, 2003; Yule, 2020).

Morphological competence refers to a writer's ability to recognize, understand, and effectively use different word-formation processes in communication. This competence is widely regarded as an important component of lexical sophistication and overall academic language proficiency (Booij, 2019; Schmitt, 2010). Writers with strong morphological awareness are generally better able to select appropriate vocabulary, construct complex word forms, and vary their lexical choices according to context and communicative purpose. Effective use of morphological structures contributes to lexical richness, textual cohesion, and the formal style expected in academic writing (Matthews, 2002; Plag, 2018). Furthermore, morphological patterns can provide valuable insights into a writer's linguistic proficiency because the ability to manipulate affixation, compounding, and derivational forms reflects not only grammatical knowledge but also rhetorical and stylistic awareness. For this reason, morphological analysis offers a useful framework for examining and comparing the linguistic characteristics of AI-generated and human-written academic texts in the present study.

2.1 AI-Generated Academic Writing

Artificial intelligence (AI)-generated writing refers to texts produced through machine learning and natural language processing technologies. These systems are trained on large collections of text and generate responses by predicting the most probable sequence of words based on the given context (Russell & Norvig, 2021). Rather than relying on genuine understanding or communicative intention, AI language models produce language through statistical prediction mechanisms. Consequently, the vocabulary, sentence structures, and discourse patterns found in AI-generated texts largely reflect the linguistic patterns present in their training data (Manning & Schütze, 1999; Jurafsky & Martin, 2023).

Recent advances in AI have significantly improved the ability of language models to generate grammatically accurate, coherent, and well-organized texts. Transformer-based architectures enable these systems to process contextual information effectively and maintain consistency across longer passages of writing (Vaswani et al., 2017; Jurafsky & Martin, 2023). As a result, AI-generated texts often resemble human academic writing in terms of fluency and structural organization. However, because AI systems are designed to maximize linguistic predictability, their outputs frequently exhibit standardized expressions, formulaic language patterns, and limited stylistic variation (Russell & Norvig, 2021; Manning & Schütze, 1999).

From a morphological perspective, AI-generated writing often relies on common word-formation patterns and high-frequency academic vocabulary. Language models tend to reproduce familiar derivational forms, affixation patterns, and conventional compound expressions that frequently occur in training data (Jurafsky & Martin, 2023; Vaswani et al., 2017). Although these features contribute to grammatical consistency and academic formality, they may limit lexical diversity and contextual flexibility. Therefore, morphological analysis provides a useful framework for examining the linguistic characteristics of AI-generated texts and identifying differences between machine-produced and human-written academic discourse (Manning & Schütze, 1999; Russell & Norvig, 2021).

2.2 Human Academic Writing

Human academic writing is fundamentally shaped by the cognitive and communicative abilities that characterize human language use. Scholars have long recognized academic writing as a purposeful and intellectually driven activity that extends beyond the production of grammatically correct sentences (Hyland, 2019; Bazerman, 2016). Effective academic writing requires the integration of critical thinking, disciplinary knowledge, and rhetorical awareness, all of which contribute to the development of a writer's individual voice and engagement with academic conventions. Human writers approach writing as a process of meaning construction, drawing on their knowledge, experiences, and understanding of context to communicate ideas effectively to specific audiences. This purposeful and reflective nature of human writing distinguishes it from texts generated through algorithmic processes (Bazerman, 2016; Flowerdew, 2022).

A key characteristic of human academic writing is its lexical diversity and morphological flexibility. According to Bauer (2003) and Schmitt (2010), skilled writers are able to select and adapt language creatively to meet particular communicative goals. This ability allows them to use derivational affixes productively, create precise compound expressions, and vary vocabulary according to disciplinary and rhetorical demands. Such flexibility is supported by morphological awareness, which enables writers to choose contextually appropriate words, employ synonyms effectively, and manipulate word forms to achieve specific stylistic and communicative purposes. As a result, human-written academic texts often display greater linguistic variety and contextual sensitivity than mechanically generated discourse (Flowerdew, 2022; Bazerman, 2016).

In addition, human academic writing is closely influenced by the social and disciplinary contexts in which it is produced. Hyland (2019) and Bazerman (2016) emphasize that academic writing competence develops through active participation in disciplinary communities, where writers learn the conventions, terminology, and rhetorical practices valued within their fields. This experience enables writers to make informed decisions regarding register, tone, and vocabulary selection according to audience expectations and communicative objectives. Consequently, human academic discourse is often characterized by contextual awareness, stylistic individuality, and deeper communicative meaning. These qualities emerge from human experience, critical reflection, and social interaction, making human-written texts more adaptable and nuanced than language generated through statistical prediction alone (Schmitt, 2010; Flowerdew, 2022).

3. RESEARCH METHOD

This study adopted a qualitative descriptive design combined with a comparative approach to investigate the morphological characteristics of AI-generated English texts and human academic writing. The qualitative descriptive design was selected because the primary objective of the study was to identify, describe, and interpret morphological phenomena found in naturally occurring written discourse rather than to test hypotheses through statistical procedures (Creswell & Creswell, 2018; Ary et al., 2019). This approach is widely applied in linguistic research as it enables researchers to examine language features in their authentic contexts and provide detailed explanations of linguistic patterns. In addition, the comparative aspect of the research design facilitated a systematic examination of similarities and differences between AI-generated and human-written academic texts. Through this comparison, the study aimed to reveal distinctive patterns of word formation and morphological usage that characterize each type of academic discourse (Creswell & Creswell, 2018).

The data consisted of ten English academic texts divided into two categories: five texts generated by OpenAI's ChatGPT and five texts written by human authors. The AI-generated texts were produced using academic writing prompts related to education and language learning, ensuring that the generated outputs reflected typical academic discourse created by contemporary AI language models. The human-written texts were selected from university student essays and journal articles that addressed comparable topics within the fields of education and applied linguistics. To ensure consistency and comparability, all texts were purposively chosen based on four criteria: relevance to the research focus, similarity of academic themes, comparable text length, and consistency in academic style. Each text contained approximately 800 to 900 words, resulting in a corpus of about 8,500 words. Purposive sampling was considered appropriate because the selected texts directly supported the objectives of the study and provided relevant data for morphological comparison (Sugiyono, 2020; Ary et al., 2019).

Data collection was conducted through documentation, a technique that involves collecting and examining written materials as sources of research data (Ary et al., 2019). This method was suitable because the study focused entirely on written texts and did not require interviews, observations, or experimental procedures. The data collection process consisted of several stages. First, academic topics related to education and language learning were selected to serve as the basis for both text generation and text selection. Second, five academic texts were generated using ChatGPT through standardized prompts. Third, five human-written academic texts discussing similar topics were gathered from student essay collections. After all texts had been collected, they were categorized into AI-generated and human-written datasets and carefully reviewed to ensure their relevance and suitability for analysis. To maintain consistency and reduce contextual variation, all selected texts were written in English and represented comparable forms of academic discourse (Sugiyono, 2020).

The data were analysed using qualitative content analysis, which is a systematic method for identifying, categorizing, and interpreting meaningful patterns within textual data (Krippendorff, 2019). This method was chosen because it provides a structured framework for examining linguistic features and allows researchers to develop deeper interpretations of language use beyond simple description. The analytical procedure followed the stages proposed by Miles, Huberman, and Saldaña (2014), namely data condensation, data display, and conclusion drawing. During the data condensation stage, words containing morphological processes were identified and extracted from all texts. In the data display stage, the identified items were organized into specific categories, including derivational affixes, inflectional affixes, compounds, blends, clippings, acronyms, and lexical patterns, based on established morphological theories (Lieber, 2016; Yule, 2020). This classification enabled a systematic comparison of morphological features across both datasets. In the final stage, the findings were interpreted by connecting the observed patterns to relevant theories of morphology and previous studies on AI-generated and human academic writing. Throughout the research process, the researchers functioned as the primary instrument of analysis and interpretation, consistent with the principles of qualitative inquiry (Creswell & Creswell, 2018). The results are presented through descriptive explanations, textual examples, frequency comparisons, and analytical tables to provide a comprehensive understanding of the morphological differences between AI-generated and human-written academic discourse.

4. RESULT AND DISCUSSION

4.1 Result

In this section, morphological features were identified and organized into five analytical categories: derivational affixes, inflectional affixes, compounding, acronyms, and lexical patterns. The findings are presented category by category before being brought together in a discussion that responds directly to the three research objectives: identifying morphological differences between AI-generated and human-written texts, examining how AI language models construct academic discourse at the word-formation level, and determining whether morphological analysis can effectively distinguish machine-produced from human-written academic texts.

Table 1. Distribution of Morphological Processes in Human and AI Texts

Morphological Process	AI-Generated Texts	Human-Written Texts
Derivational Affixes	186	154
Inflectional Affixes	142	137
Compounding	48	61
Acronyms	32	24
Lexical Repetition	79	34

The table 1 indicates that AI-generated texts recorded higher frequencies of derivational affixes and markedly greater lexical repetition, while human-written tests showed more varied compounding and considerably lower vocabulary recurrence. These overall patterns point toward meaningful differences in how each text type deploys morphological resources, and they are examined in greater depth in the sections that follow.

4.1.1 Derivational Affixation

Derivational affixation emerged as the most frequent morphological process across both text types, though notable differences were observed in the range and complexity of forms used. AI-generated texts recorded 186 instances of

Vol. 8 No. 1
June 2026
e- ISSN 2685 - 0559
p- ISSN 2684 - 673X
IdeBahasa
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derivational affixation, compared with 154 in human-written texts. Beyond this quantitative difference, however, the more revealing distinction lay in the variety of derivational forms employed. The AI-generated corpus was dominated by a narrow cluster of suffixes — principally *-tion*, *-ment*, *-ity*, *-ness*, and *-ly* — which appeared with striking regularity across all five texts. Words such as *communication*, *development*, *flexibility*, *effectiveness*, and *significantly* recurred persistently throughout the dataset, suggesting a strong preference for a limited set of formally acceptable academic word forms as shown from the table 2.

Table 2. Frequency of Derivational Suffixes in AI-Generated Texts

Suffix	Examples	Frequency
-tion	communication, interaction, education	52
-ment	development, improvement, achievement	39
-ity	flexibility, creativity, ability	31
-ness	effectiveness, awareness	24
-ly	significantly, effectively	40

Human-written texts, while recording a slightly lower overall count of derivational forms, displayed considerably greater morphological complexity. Rather than relying on a fixed set of suffixes, human writers combined multiple affixes to construct layered derivational forms that responded to specific communicative and contextual demands. Words such as *misinterpretation* (*mis-* + *interpret* + *-ation*), *unpredictability* (*un-* + *predict* + *-ability*), *interdisciplinary* (*inter-* + *discipline* + *-ary*), and *underrepresentation* (*under-* + *represent* + *-ation*) exemplify this capacity for morphologically complex word construction.

These findings point to a clear morphological difference between the two text types at the derivational level. Whereas AI-generated texts favour a predictable and repetitive suffix repertoire that sustains surface academic formality, human-written texts draw upon a wider and more flexible range of derivational processes that reflect genuine disciplinary and rhetorical awareness. This difference is directly relevant to the first research objective, establishing derivational affixation as one of the most diagnostically useful morphological dimensions for distinguishing between AI-generated and human-written academic discourse.

4.1.2 Inflectional Affixes

Both AI-generated and human-written texts demonstrated consistent and accurate use of inflectional affixes throughout the corpus. Common inflectional forms identified across both datasets included plural markers (*-s*/*-es*), past tense markers (*-ed*), progressive aspect markers (*-ing*), and third-person singular present markers (*-s*). Frequencies were closely matched, with AI-generated texts yielding 142 instances and human-written texts 137. Illustrative examples from the AI-generated corpus — such as students learn through technology-integrated activities, researchers analyzed writing texts, and learning environments are developing rapidly — confirm that AI systems handle inflectional morphology with a high degree of grammatical accuracy. Human-written texts displayed equally accurate inflectional usage, though with marginally greater flexibility in tense and aspect selection across varying rhetorical contexts.

The near-identical frequencies and comparable accuracy observed at the inflectional level indicate that this morphological category does not constitute a meaningful point of differentiation between the two text types. The capacity of transformer-based language models to maintain grammatical consistency across extended passages adequately accounts for this equivalence (Vaswani et al., 2017; Jurafsky & Martin, 2023). In relation to the first research objective, therefore, inflectional morphology represents a domain of convergence rather than divergence — one in which both AI-generated and human-written texts perform with comparable proficiency. This finding suggests that meaningful morphological differentiation between the two text types must be sought at the derivational, lexical, and compounding levels, where the limitations of statistical language generation become more linguistically apparent.

4.1.3 Compounding

The analysis of compounding yielded differences that are relevant to both the first and second research objectives. Human-written texts recorded 61 compound instances against 48 in AI-generated texts, and the nature of the compounds identified across the two datasets differed considerably. AI-generated texts relied predominantly on a set of recurring standard academic compounds — including *language model*, *learning process*, *academic writing*, and *technology integration* — which appeared across multiple texts with little variation in form or application. Human-written texts, by contrast, featured a much wider array of context-sensitive and discipline-specific compounds, among them *problem-solving strategy*, *cross-cultural communication*, *knowledge-construction process*, and *self-regulated learning*.

Table 3. Comparison of Compound Types in AI-Generated and Human-Written Texts

Compound Type	AI-Generated Texts	Human-Written Texts
Standard Academic Compounds	39	24
Context-Specific Compounds	9	37

This contrast in compounding behavior sheds light on how AI language models construct academic discourse at the word-formation level — the focus of the research objective. The dominance of standard academic compounds in AI-generated texts suggests that language models treat compounding not as a productive creative process but as the retrieval of pre-formed lexical units that recur frequently in academic training data. Human writers, on the other hand, demonstrated an ability to construct compounds that were tailored to specific disciplinary concepts and communicative purposes, reflecting the kind of morphological creativity and contextual sensitivity that Bauer (2003) and Plag (2018) associate with skilled academic language use. This distinction reinforces the view that AI systems construct academic vocabulary by reproducing statistically familiar patterns rather than by generating morphologically novel expressions in response to meaning-making demands.

4.1.4 Lexical Patterns and Vocabulary Variation

Of all the morphological categories examined, lexical repetition produced the sharpest quantitative contrast between the two text types, and it is in this domain that the word-formation tendencies of AI language models are most clearly exposed. AI-generated texts recorded 79 instances of lexical repetition — more than twice the 34 instances found in human-written texts. A small number of high-frequency academic words, namely *learning*, *technology*, *significant*, *effective*, and *development*, appeared with conspicuous regularity throughout the AI-generated corpus, as shown in Table 4.

Table 4. Frequency of Repeated Lexical Items in AI-Generated Texts

Repeated Word	Frequency
learning	26
technology	21
significant	18
effective	16
development	15

This pattern of persistent lexical repetition is a direct consequence of how AI language models construct text at the word-formation level. By assigning the highest probability to vocabulary items that appear most frequently in academic contexts within their training data, these systems consistently return to the same lexical choices rather than generating varied alternatives, regardless of whether greater diversity would better serve the communicative purpose of a given passage (Manning & Schütze, 1999; Russell & Norvig, 2021). This finding addresses the second research objective by demonstrating clearly that AI systems construct academic discourse through statistical reproduction of high-frequency word forms rather than through deliberate, context-driven lexical selection.

Human writers approached vocabulary selection in a markedly different way. Rather than repeating a single word such as *important* throughout a text, human writers drew upon a range of synonymous expressions — including *essential*, *crucial*, *fundamental*, and *pivotal* — choosing among them according to the precise rhetorical emphasis required at each point in the text. This practice of lexically varied substitution reflects the morphological awareness and communicative judgment that Schmitt (2010) and Flowerdew (2022) regard as central to proficient academic writing. It contributes directly to the lexical richness and stylistic depth that differentiate authentic human academic discourse from the more uniform and repetitive outputs of AI-driven text generation.

4.2 Discussion

The findings of this study present a detailed and layered picture of how AI-generated and human-written academic texts differ morphologically. Examining the data across all five analytical categories reveals that the two text types consistently produced distinct morphological profiles throughout the corpus. The most substantial contrasts were concentrated in three areas — derivational complexity, compounding variety, and lexical diversity — while both text types performed at a broadly comparable level in terms of inflectional accuracy. Although this grammatical equivalence at the inflectional level might initially suggest a degree of linguistic parity between the two, it does not hold across the broader morphological domain, where the differences between machine-produced and human-written discourse are both measurable and analytically significant. These overall patterns provide a solid empirical basis from which to address each of the research objectives.

In relation to the research objective of identifying morphological differences between the two text types, the evidence is both consistent and wide-ranging. AI-generated texts were characterised by a morphologically uniform profile — one defined by a restricted range of derivational suffixes, the repeated use of standardised compound expressions, and a persistent reliance on a limited pool of high-frequency academic words. Human-written texts presented a strikingly different picture, displaying greater morphological depth through the use of complex multi-affix constructions, discipline-sensitive compounds, and a noticeably broader vocabulary achieved through deliberate synonym selection. Crucially, these contrasts were not confined to any single morphological category but manifested consistently across derivational affixation, compounding, and lexical variation alike, indicating that the morphological gap between AI-generated and human-written texts is systematic and pervasive rather than selective or coincidental. Such findings are in accordance with Booij (2019) and Schmitt (2010), both of whom link morphological variety and structural complexity to higher levels of linguistic proficiency and communicative competence in academic writing.

The derivational affixation patterns identified in AI-generated texts merit closer examination, as they shed the most direct light on how these systems approach word formation. The heavy concentration of suffixes such as *-tion*, *-ment*, *-ity*, and *-ly* throughout the AI-generated corpus points to a strong and consistent preference for nominalised and adverbialised forms that appear with high frequency in formal academic writing. Although such forms are grammatically sound and contextually appropriate, their repetitive application across the dataset implies that AI systems select derivational forms primarily on the basis of statistical recurrence rather than genuine communicative need. Human writers, by contrast, demonstrated far greater morphological inventiveness, producing elaborate multi-affix constructions — such as *unpredictability* and *interdisciplinary* — that were clearly tailored to the specific conceptual and rhetorical demands of their writing contexts. The ability to deploy such forms accurately and appropriately reflects a level of word-formation command that Lieber (2016) and Bauer (2003) associate with advanced morphological competence — a competence that AI systems, for all their grammatical proficiency, have not yet demonstrated.

With respect to the research objective of examining how AI language models construct academic discourse at the word-formation level, the findings point to a clear and structurally predictable pattern. AI systems do not generate morphological forms in response to meaning or context; rather, they reproduce the word-formation patterns that are most statistically prevalent in their training data. The outcome is writing that projects a veneer of academic formality through morphological repetition while remaining largely detached from the creative and context-driven lexical choices that define skilled human academic writing. Jurafsky and Martin (2023) and Russell and Norvig (2021) account for this tendency by explaining that language models function by identifying the most probable word sequence given a preceding linguistic context — a mechanism that systematically privileges familiar derivational forms, pre-existing compound expressions, and high-frequency vocabulary over morphologically inventive or discipline-specific alternatives. The AI-generated texts analysed in this study clearly embody this logic, revealing that morphological predictability is not a peripheral or incidental quality of machine-produced writing but an inherent outcome of the statistical processes through which such texts are constructed.

Further support for this interpretation comes from the compounding and lexical repetition data, both of which reflect the same underlying mechanism of statistical reproduction. The prevalence of generic academic compounds — such as *language model*, *learning process*, and *technology integration* — in AI-generated texts, accompanied by the near-total absence of context-specific constructions, strongly suggests that AI systems approach compounding as the retrieval of ready-made lexical units rather than as a generative morphological activity. In a parallel fashion, the high recurrence of words such as *learning*, *technology*, and *significant* at frequencies more than twice those found in human-written texts confirms that AI text generation is oriented toward lexically predictable output rather than toward meaningful variety. Human writers, by contrast, drew consistently on their disciplinary background, experiential knowledge, and rhetorical awareness to make more discerning and varied word choices, resulting in texts that were demonstrably richer in both morphological complexity and communicative nuance. These are precisely the qualities that Hyland (2019) and Flowerdew (2022) identify as hallmarks of authentic academic writing — qualities that emerge from human cognition and lived experience rather than from algorithmic calculation.

Addressing the research objective of determining whether morphological analysis can effectively distinguish machine-produced from human-written academic texts, the evidence collected in this study offers a clear and compelling affirmative response. A consideration of the full morphological profile of each text type — taking into account derivational range and complexity, the character of compounding patterns, and the degree of lexical variation — reveals a consistent and dependable basis for differentiation. It bears noting, however, that not every morphological category contributes equally to this discriminatory capacity. As the inflectional analysis demonstrated, grammatical accuracy at the inflectional level is shared by both text types and therefore offers little diagnostic value on its own. The analytical strength of morphological analysis as a differentiating tool is realised most fully when derivational complexity, compounding specificity, and lexical diversity are considered together as an integrated morphological profile rather than as isolated variables.

Viewed in its entirety, the evidence from this study firmly establishes morphological analysis as a principled, sensitive, and theoretically well-grounded method for distinguishing AI-generated from human-written academic discourse. Human academic writing, as the findings consistently demonstrate, possesses a degree of morphological richness, contextual responsiveness, and lexical creativity that AI systems — bound as they are by probabilistic generation mechanisms — are currently unable to reproduce. Although AI-generated writing attains a level of grammatical correctness and structural organisation that renders it superficially similar to human academic prose, it falls demonstrably short at the deeper morphological level where authentic communicative purpose, disciplinary expertise, and rhetorical sensibility leave their most telling linguistic marks. These findings add meaningfully to the growing body of research on the linguistic dimensions of AI-generated academic writing, and they reaffirm the irreplaceable role of human linguistic creativity and contextual judgment in the construction of academically credible and communicatively effective discourse

(Hyland, 2019; Bazerman, 2016; Booij, 2019).

5. CONCLUSION

In conclusion, the findings revealed clear and consistent morphological distinctions between the two text types. AI-generated texts were defined by a narrow and repetitive morphological profile, most visibly expressed through the overuse of a small set of derivational suffixes, the recurrence of formulaic academic compounds, and the persistent repetition of high-frequency vocabulary items. These patterns are a direct reflection of how AI language models operate — constructing text through statistical prediction rather than through meaningful communicative engagement with context, audience, or disciplinary purpose. Human-written texts, in contrast, demonstrated considerably greater morphological breadth and adaptability, characterized by complex multi-affix word constructions, context-sensitive compounding, and a richer vocabulary range made possible through informed synonym selection. The sole area of convergence between the two text types was inflectional morphology, where comparable levels of grammatical accuracy were observed across both datasets — a finding that cautions against relying on surface grammatical correctness as a sufficient basis for distinguishing AI-generated from human-written academic prose. Collectively, the findings affirm that a combined morphological examination of derivational complexity, compounding patterns, and lexical diversity provides a dependable and linguistically principled means of differentiating between the two text types.

The implications of these findings extend meaningfully to educators, researchers, and institutional policymakers alike. For teachers and lecturers operating in higher education, the results highlight the value of integrating explicit morphological instruction into academic writing curricula. Guiding students to understand how derivational processes, compounding strategies, and lexical variation contribute to the overall quality of academic writing can significantly strengthen their capacity to produce discourse that moves beyond grammatical correctness toward genuine linguistic sophistication and communicative depth. Equally, familiarity with the morphological tendencies of AI-generated writing can sharpen educators' ability to recognize machine-produced submissions and engage with them in ways that are academically informed and pedagogically productive.

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