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Tracing Artificial Intelligence in EFL Student Writing: A Linguistic Approach to Identifying Machine-Assisted Text in Undergraduate Writing

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Abstract
As AI-assisted writing tools become more present in university classrooms, the nature of students' written work in EFL contexts is quietly shifting. These developments raise new questions about who is responsible for the final text, how students build their writing abilities, and how they develop a sense of voice in their academic work. Although interest in the ethical and pedagogical implications of AI is increasing, we still know little about how and where AI-shaped textual patterns actually appear in student writing. This study investigates the linguistic and stylistic traces of AI assistance in undergraduate academic work and highlights the need for fair, transparent assessment practices and informed pedagogical support in AI-integrated learning environments. Using a qualitative corpus of 557 undergraduate texts, the study applied a three-cycle coding process supported by descriptive linguistic measures. This approach offers a detailed view of textual patterns by focusing on the features found in students' actual writing, moving beyond the self-report surveys and tool-detection methods commonly used in earlier research. The findings reveal recurring tendencies, including reduced sentence-length variation, over-explicit cohesion, generic macro-structural framing, and a polished yet impersonal tone. These tendencies point to a mixed effect: AI tools seem to improve cohesion and linguistic accuracy, yet they can also blur students' individual voice and weaken the texture of their arguments. The study offers evidence that can help educators and institutions make sense of AI's growing role in student writing and develop assessment and teaching practices that fit their pedagogical and institutional realities.

Keywords: AI-assisted academic writing, authorship, EFL writing assessment, stylistic traces, textual identity
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Introduction

AI-assisted writing tools, from generative systems like ChatGPT to corrective applications such as Grammarly and QuillBot, are increasingly shaping how academic texts are produced in higher education (Crosthwaite, 2025; Hui & Dang, 2024; Mugableh, 2024). In this study, AI-assisted writing refers to student texts produced with the support of generative or corrective AI technologies, whether for content generation, paraphrasing, linguistic correction, or stylistic refinement. These tools offer immediate feedback, improve linguistic accuracy, and help students produce fluent, well-organized texts with reduced cognitive effort (Moussa & Belhiah, 2024). For many undergraduate writers, particularly in English as a Foreign Language (EFL) contexts, such support acts as an accessible form of scaffolding that improves confidence and facilitates engagement with academic discourse (Ali, 2024; Söğüt, 2024). Yet, the growing normalization of AI use has also intensified concerns related to authorship, originality, and the long-term development of independent writing competence, prompting renewed debate about academic integrity and student writing in higher education (Committee on Publication Ethics, 2023; Humble, 2025).

Although research on AI in education has expanded rapidly, much of it has centered on students' perceptions, ethical considerations, or institutional and policy responses (Crosthwaite, 2025; Alawad, 2025). By contrast, far fewer empirical studies have examined the texts themselves to document how AI assistance becomes linguistically or stylistically traceable in student writing. As a result, limited evidence exists regarding which textual features may differentiate AI-assisted writing from independent student work or how such traces appear in authentic academic assignments (Desaire et al., 2023; Wu et al., 2025). This gap is especially noticeable as educators seek evidence-based frameworks for assessment, authorship verification, and instructional practice in increasingly AI-rich learning environments (Waked et al., 2024; Weber-Wulff et al., 2023).

The present study responds to this need by conducting a large-scale qualitative analysis of N = 557 undergraduate writing samples to identify linguistic and stylistic features that may indicate AI mediation. It investigates which textual characteristics appear to reveal potential traces of AI assistance and examines how these features manifest across a substantial corpus through qualitative analysis. The study aims to analyze recurrent linguistic and stylistic tendencies associated with AI mediation, to describe patterns in vocabulary, cohesion, stance, and rhetorical framing, and to develop a descriptive framework that can help educators recognize AI-influenced writing without relying on punitive or unreliable detection mechanisms.

The aim of this research is to offer an evidence-based, pedagogically useful view of how AI use influences student writing at the level of language. By documenting textual tendencies associated with AI-assisted writing, the study aims to inform classroom practice, support the development of AI literacy, and help higher education institutions promote ethical, transparent engagement with digital tools while strengthening students' independent academic voice and writing competence. In doing so, it addresses a timely need for evidence that can guide educators, policy makers, and writing specialists as they navigate the complex landscape of AI-mediated academic writing.

Literature Review

Generative AI and Student Writing

Generative AI has become deeply embedded in everyday writing activity across higher education, shaping how students plan, draft, and revise academic texts. Recent studies in EFL

contexts report measurable gains in fluency, accuracy, and surface-level quality when learners use tools such as ChatGPT for feedback or scaffolding, with improvements observed in coherence, error reduction, and overall text clarity (Barrot, 2024; Mahapatra, 2024; Mekheimer, 2025; Polakova & Ivenz, 2024). Across this literature, AI is consistently positioned as a writing assistant rather than a full author, with its strongest influence found at the level of sentence correctness, cohesion, and rhetorical organization rather than deeper ideational development or evidence-based argumentation (Seo, 2024; Söğüt, 2024; Wang & Dang, 2024). Sector reports likewise document a rapid normalization of AI support on university campuses and evolving staff development efforts aimed at addressing its pedagogical and ethical implications (Alshreef & Saaty, 2025).

Stylistic Convergence and "Algorithmic Cohesion"

Comparative and stylometric research across HCI, NLP, and writing studies converges on a set of recurring tendencies in AI-mediated prose. These include compressed variation in sentence length, high syntactic correctness, explicit and frequent transition markers, generic framing patterns, and a polished yet impersonal register (Emara, 2025; Gosar et al., 2025; Khan et al., 2025; Opara, 2024). Such signatures have been repeatedly identified as relatively stable across models, even as specific detector thresholds vary (Opara, 2025). For novice writers, these features can provide welcome structure and clarity; nevertheless, they also blur distinctions between human-produced and AI-assisted text. The same attributes that help learners, such as tidy transitions, predictable cadence, and a formal tone, are often those most strongly associated with algorithmic mediation.

The Fragility and Risks of AI-Text Detection

Recent work in this area encourages a careful approach to the use of automated AI text detection tools. Researchers have noted that these systems often deliver uneven results, and their accuracy can shift with the topic, the type of task, or the overall length of the writing sample (Elkhatat et al., 2023; Pratama, 2025). Other investigations, including technical reviews and case-based reports, describe persistent concerns such as high false positive rates, bias linked to particular fields of study, and the ease with which a text can be altered enough to avoid detection. As a result, many scholars caution against treating these tools as firm evidence of academic misconduct (Gotoman et al., 2025; Perkins et al., 2024). In educational settings, this reliance may expose students to unjust claims and weaken trust in assessment practices. For these reasons, a growing body of literature encourages a shift toward process-based evaluation, close reading of writing traces, and honest reflection by learners, rather than depending on automated detection as the sole indicator of authorship.

Ethics, Authorship, and Disclosure

Ethical guidelines in academic writing consistently affirm two principles: AI cannot be listed as an author, and human writers remain fully responsible for all content produced with or without AI support (COPE, 2023). Discipline-specific recommendations further encourage educators to teach students how to evaluate when and why AI use is appropriate, moving away from blanket prohibitions toward critical and transparent engagement (Chan, 2023; Fodrey & Girdharry, 2025). Parallel discussions in writing studies critique metaphors of "AI co-authorship," arguing instead for reflective authorship that treats AI as a tool rather than a collaborator (Crosthwaite, 2025; Watson et al., 2025). These views support a shift toward understanding academic integrity as a

process, centered on transparency, reflection, and attribution, and mirror policy analyses calling for adaptable, pedagogy-first institutional guidelines with clear communication to students (Alsharefeen & Al Sayari, 2025; Balalle & Pannilage, 2025; Dwivedi et al., 2023).

Implications for EFL and Higher Education Assessment

Many EFL teachers have noticed that AI tools can help students produce writing that looks cleaner and more coherent than what they usually create on their own. This can be helpful, of course, but it also means that grammatical accuracy and smooth transitions may give an inflated sense of a learner's real proficiency. Several studies with EFL groups and with Gen Z students report that AI support often improves the clarity and overall organization of early drafts, yet the same studies show very little lasting progress in deeper abilities such as developing a clear stance, recognizing an audience, or using evidence in a meaningful way (Liu et al., 2025; Mekheimer, 2025; Seo, 2024; Song and Song, 2023). As a result, assessment becomes more complicated, since polished sentences can easily hide limited rhetorical development.

Because of these concerns, national and institutional reviews have begun recommending a shift toward evaluating the writing process rather than the final product alone. This includes looking at draft histories, asking students to explain the changes they made, and requiring short statements that describe how AI was used in the assignment (Humble, 2025; ICAI, 2024; Dwivedi et al., 2023). Taken together, the recent literature moves toward a practical middle ground. It recognizes that AI is now part of everyday writing, warns against heavy reliance on detection systems, and encourages open disclosure. It also calls for closer qualitative attention to features such as vocabulary, grammar, cohesion, stance, and voice, supported by draft trails and moments of student reflection.

The literature offers meaningful contributions to our understanding of AI's pedagogical benefits, stylistic imprints, detection reliability challenges, and evolving ethical frameworks; nevertheless, few studies have examined authentic student texts at scale to document how linguistic and stylistic traces of AI assistance manifest in practice. Based on a qualitative corpus of 557 undergraduate writing samples, this study takes a closer look at how AI use shows up in the texts students produce. Instead of concentrating on attitudes or policy discussions, it moves directly into the writing and examines the linguistic patterns that appear across the corpus. This shift toward the texts themselves allows the study to offer concrete evidence that can help strengthen assessment practices, inform teaching, and guide more responsible approaches to AI use in higher education.

Methodology

Research Design

This study employed a qualitative textual analysis to examine linguistic and stylistic traces of AI assistance in undergraduate academic writing. The goal was not to determine whether a text was AI-generated, but to identify features that may indicate degrees of AI mediation. Drawing on interpretive inquiry (Denzin, 2018), the analysis focused on how textual characteristics reveal the influence of digital tools on writing practices. The approach combined corpus-based description with interpretive linguistic analysis. Quantitative measures such as sentence-length averages and lexical diversity were used to outline textual regularities, while qualitative coding and thematic interpretation helped explain the rhetorical and stylistic patterns underlying them. Triangulation between metrics and interpretive coding reinforced analytic rigor. The research was conducted at

the International University of Rabat, a multilingual Moroccan institution where English is taught as a foreign language across undergraduate programs. This setting offers a relevant EFL context: students frequently produce academic texts in English while relying on digital support tools to address proficiency gaps, making it an appropriate site for examining AI-mediated textual traces in authentic student writing.

Participants

The dataset consisted of N = 557 undergraduate writing samples, each representing an individual student's written response to the same academic task. All submissions were anonymized and collected within an EFL context at the International University of Rabat, Morocco during the academic year 2024/2025. Each text ranged from approximately 110 to 320 words, with an average length of 200 words. Purposive sampling (Patton, 2015) was applied to include complete, original texts of the same genre to ensure comparability. Incomplete drafts, duplicated submissions, or texts shorter than ten words were excluded. The resulting corpus provided a diverse yet consistent set of student texts suitable for examining linguistic and stylistic patterns. Each text was treated as a unit of analysis within the broader dataset.

Data Preparation and Processing

All texts were imported into a qualitative corpus environment for cleaning and standardization. Superficial errors such as spacing and formatting inconsistencies were normalized, but lexical and grammatical content remained untouched to preserve authenticity. Preliminary linguistic profiling was performed using basic descriptive metrics to establish the structural baseline of the corpus. These measures included:

- Word count and sentence count per text,
- Average sentence length and its standard deviation (as indicators of syntactic variation),
- Type-Token Ratio (TTR) as a measure of lexical diversity,
- Densities of specific linguistic markers, discourse connectors, hedging expressions, and generic or templated phrases.

Qualitative Coding Procedures

Data analysis followed a three-cycle qualitative coding process based on Saldaña (2021) and Braun and Clarke's (2006) guides to thematic analysis. Throughout all cycles, analytic memos were written to document reasoning and decisions, creating a transparent audit trail. Table one below presents a detailed Summary of the Coding Process.

Table 1. *Summary of the three-cycle qualitative coding process*

Cycle	Focus and Purpose	Analytic Procedures	Outcome
Cycle 1 – Open Coding	Identify observable linguistic and stylistic features that might signal AI assistance.	Each text was read line by line to note patterns such as uniform sentence lengths, repetitive connectors, overly formal tone, or absence of stance. Codes were descriptive and language-based rather than theoretical.	A comprehensive list of initial codes representing surface textual behaviors across the corpus.
Cycle 2 – Pattern Coding	Group related codes into broader analytical categories.	Individual codes were clustered into higher-order patterns (e.g., cohesion strategies, lexical variation, authorial voice, rhetorical framing). Quantitative summaries of feature frequency	A set of recurrent linguistic and stylistic categories showing cross-text consistency.

Cycle	Focus and Purpose	Analytic Procedures	Outcome
		across the 557 texts provided contextual support.	
Cycle 3 – Thematic Development	Synthesize patterns into themes capturing potential AI influence.	Higher-order categories were refined through iterative comparison of excerpts, coding memos, and linguistic metrics to ensure coherence.	Formulaic Cohesion, Polished Impersonality, Generic Framing, and Limited Lexical Breadth

Ethical Considerations

Ethical clearance was obtained from the host institution prior to data collection. Participation was voluntary, and all identifying information was removed before analysis. The study explicitly avoided punitive or surveillance-based aims: its purpose was pedagogical and descriptive, seeking to understand patterns of writing in the age of AI rather than to accuse or penalize students. Results were reported in aggregate form to protect anonymity and maintain academic integrity.

Results

Overview of the Corpus

The dataset used for analysis consisted of N = 557 undergraduate writing samples, each representing one student's original submission. All texts were anonymized and correspond to the same academic writing task, allowing comparability across the corpus. The overall linguistic profile indicated that the writing is generally fluent and syntactically well-formed, with limited variation in structure and rhythm.

Across the corpus, texts averaged approximately 200 words, ranging from 110 to 320 words. The mean sentence count was 12 per text, and the average sentence length was 17.5 words, while the standard deviation of sentence length (5.3) showed that most sentences fall within a narrow length range. The TTR averaged 0.45, reflecting moderate lexical diversity. Cohesive devices occur frequently: discourse-marker density averages 0.018, hedging density 0.015, generic-phrase density 0.007, and repetition ratio 0.11. These numerical results suggest syntactic consistency, balanced lexical choice, and heavy reliance on cohesive signals as illustrated in table two below.

Table 2. *Quantitative summary of linguistic indicators across the corpus*

Indicator	Description	Average Across Corpus	Observed Range
Word Count	Total words per student text	200 ± 45 words	110–320
Sentence Count	Number of sentences	12 ± 3	6–19
Average Sentence Length	Words per sentence	17.5	10–25
Sentence-Length Std. Dev.	Variation of sentence length	5.3	2.0–9.8
Type-Token Ratio (TTR)	Lexical diversity index	0.45	0.31–0.68
Discourse-Marker Density	Ratio of cohesive markers to total words	0.018	0.005–0.042
Hedging Density	Ratio of hedging forms to total words	0.015	0.002–0.033
Generic-Phrase Density	Stock or templated phrases	0.007	0–0.017
Repetition Ratio	Words repeated ≥ 3 times	0.11	0.03–0.22

At this descriptive level, the corpus showed a notable clustering around shared textual habits, suggesting that students produced broadly similar linguistic profiles regardless of topic or proficiency. Moderate sentence lengths, limited variation, mid-range lexical diversity, and consistent densities of discourse markers, hedges, and generic phrases point to a stable "rhythmic" pattern across the corpus. Such regularity hints at constrained stylistic choices and a tendency toward uniform cohesion strategies, patterns that warranted closer qualitative examination to understand the rhetorical and stylistic forces shaping them, including the possible influence of AI-mediated writing support.

Distribution of Linguistic and Stylistic Flags

Cycle 1 qualitative coding identified seven recurrent linguistic or stylistic features ("flags") observable across the 557 texts. Frequencies and percentages were derived from the total sample to show how often each feature appeared as seen in table three.

Table 3. *Distribution of cycle 1 linguistic and stylistic features across the corpus*

Cycle 1 Flag	Frequency (Texts)	Percentage (%)	Core Linguistic Characteristic
Uniform sentence lengths	114 / 557	20.5 %	Sentences of nearly equal length; minimal rhythm variation
High use of discourse markers	102 / 557	18.3 %	Recurrent transitional devices ("however", "therefore", "in conclusion")
Generic / templated phrases	86 / 557	15.4 %	Stock openings ("in today's world", "people have always")
Unusually polished and uniform tone	74 / 557	13.3 %	Grammatically flawless, stylistically neutral language
Lexical repetition	59 / 557	10.6 %	Reuse of same words ≥ 3 times within short segments
Low lexical diversity for length	51 / 557	9.2 %	Long texts using narrow vocabulary range
Heavy hedging / neutral stance	37 / 557	6.6 %	Frequent "may", "might", "it seems", producing impersonal tone

The distribution shows that structural regularity (uniform sentence lengths) and cohesive saturation (high use of discourse markers) are the most prevalent textual characteristics, occurring in roughly one-fifth of all submissions. Generic phrasing and polished tone follow closely, suggesting a large proportion of texts share similar stylistic signatures.

Sub-Patterns Within Each Flag

Closer textual examination of representative samples revealed further details within each flagged category:

- **Uniform sentence lengths (20.5 %)** : Sentences typically ranged between 15 and 20 words, with limited clause variation. Paragraphs tended to progress in evenly sized units of meaning, rarely employing complex subordination or sentence fragments.
- **High use of discourse markers (18.3 %)** : Writers often used connectors at the beginning of nearly every sentence ("Moreover" / "Therefore" / "In conclusion"). In several texts, transitional devices appeared in successive lines, producing highly explicit cohesion.

- **Generic or templated phrases (15.4 %)** : Formulaic openings and closings occurred widely. Common expressions included *"In today's world"*, *"Since the beginning of time"*, and *"It is important to note that"*.
- **Unusually polished and uniform tone (13.3 %)** : Texts were almost entirely free from grammatical or mechanical errors. Punctuation and capitalization were consistently correct, and vocabulary choices remained within formal registers.
- **Lexical repetition (10.6 %)** : Certain key nouns or adjectives reappeared multiple times in close proximity, usually without semantic expansion, such as repeating *"important"*, *"problem"*, *"society"*.
- **Low lexical diversity for length (9.2 %)** : Longer texts relied heavily on a restricted lexical set, with minimal introduction of synonyms or paraphrasing beyond function-word variation.
- **Heavy hedging or neutral stance (6.6 %)** : A subset of texts contained repeated modal and evidential expressions ("may", "might", "it appears that") producing a linguistically cautious voice.

These micro-patterns provide a richer picture of how individual linguistic habits manifest across the large dataset.

Thematic Grouping of Recurrent Patterns

Subsequent pattern coding consolidated the above features into four broader themes that describe clusters of co-occurring behaviors. Each theme included several of the previously identified flags as highlighted in table four.

Table 4. *Thematic categories emerging from cycle 2 and cycle 3 analysis*

Theme	Description	Representative Features	Typical Frequency Range (%)
Formulaic Cohesion	Heavy reliance on explicit connective markers producing tightly linked sentence transitions.	High use of discourse markers; uniform sentence lengths	18–21 %
Polished Impersonality	Grammatically precise but emotionally detached and stance-neutral expression.	Polished tone; heavy hedging; limited self-reference	13–14 %
Generic Framing	Recurrence of prefabricated openings and generalizing statements that introduce or conclude essays.	Generic phrases; fixed introductory structures	15 %
Limited Lexical Breadth	Restricted vocabulary range combined with repetition of key terms within paragraphs.	Lexical repetition; low lexical diversity	9–11 %

Discussion

The patterns emerging from the corpus draw a clear picture of how AI mediation leaves its imprint on student writing. Consistent sentence structures, constrained lexical variety, and uniform cohesion reveal a stylistic convergence characteristic of algorithmic support, while qualitative patterns such as muted voice, standardized framing, and diminished rhetorical individuality expose its influence at deeper discourse levels. These tendencies trace the pathways through which AI shapes both the surface texture and the rhetorical architecture of undergraduate texts, providing a natural entry point into the interpretive analyses that follow.

Linguistic and Stylistic Implications

The linguistic profile of the 557 undergraduate texts revealed a striking balance between fluency and homogeneity. The dominance of regular sentence patterns, moderate lexical diversity, and consistent cohesion points to writing that is technically proficient but stylistically restrained. This surface uniformity reflects what several scholars have described as the algorithmic aesthetic of AI-mediated language: texts that prioritize grammaticality, clarity, and flow while suppressing individuality and rhetorical experimentation (Cowls et al., 2023; Lee, 2024).

In contexts where students are still developing advanced writing skills, such consistency may not naturally emerge without external scaffolding. The presence of features such as uniform sentence length and high discourse-marker density indicates that many compositions follow the syntactic cadence typical of machine-generated output: symmetrical clauses joined by transitional markers. These patterns align with corpus-based studies of LLM-generated text, which often demonstrate compressed sentence-length variance and over-explicit cohesion (Milička et al., 2025; Muñoz-Ortiz et al., 2024; Reinhart et al., 2024). In the current dataset, nearly one-fifth of texts exhibited this combination, suggesting that either direct generation or heavy post-editing through AI tools contributed to the final form.

Lexical analysis further reinforces this trend. The average TTR of 0.45 and the recurrence of high-frequency adjectives such as *important, global, and social* reveal a reliance on generic lexical items common in AI-produced academic prose (Fredrick Craven, 2025; Kasneci et al., 2023; Reviriego et al., 2024). Such diction achieves universality and readability but rarely demonstrates depth of semantic selection. This finding supports the argument that AI assistance tends to normalize lexical choice, reducing idiosyncrasy and blurring distinctions between individual writers.

Authorship, Originality, and the Question of Voice

The textual patterns observed raise broader concerns about authorship and ownership of language in academic settings. The polished yet impersonal tone that characterized roughly 13 percent of the corpus typifies the “voice flattening” phenomenon: a process through which AI assistance erodes linguistic traces of personal stance. The absence of self-referential pronouns, cautious modality, and detached phrasing together create an “institutional voice” that sounds correct but lacks positionality (Ji et al., 2024; Malik et al., 2024).

In undergraduate writing, where students are expected to develop an academic identity through language (Li, 2024; Rahman et al., 2024), this neutralization of stance can obscure evidence of cognitive engagement. The recurring use of hedging (*may, might, could, it seems that*) across multiple texts illustrates how AI tools favor balanced formulations over argumentative risk. What appears is writing that meets formal academic conventions but does not reveal the writer’s reasoning process.

The generic framing, especially the templated openings “In today’s world” signals the automation of rhetorical invention. Instead of crafting context-specific introductions, students appear to adopt prefabricated rhetorical shells. This practice echoes the prompt-based paraphrasing behavior reported in educational studies (Iqbal & Abul Kashem, 2023), where learners feed outlines into AI systems that generate generic introductions and conclusions later edited for coherence. As a result, the boundaries between assistance, collaboration, and authorship become blurred: the text is authored by the student, yet its rhetorical scaffolding may originate from an algorithmic model.

These findings point to an emerging paradox. On one hand, AI-mediated writing enables syntactic mastery and reduces language anxiety; on the other, it diminishes the presence of authentic voice, which is exactly what educators aim to cultivate. Therefore, the concept of originality in writing must evolve from sole textual production to reflective authorship: the student's ability to critically control and disclose the degree of technological mediation.

Pedagogical and Institutional Implications

From a pedagogical standpoint, the patterns identified in this corpus call for a fundamental shift in how writing instruction and assessment address AI tools. Traditional approaches to plagiarism or "AI detection" risk misinterpreting polished but legitimate writing as inauthentic. Instead, the data support a pedagogy of disclosure and reflection (Knox, 2025), in which students are guided to articulate how and why they use AI systems rather than conceal their use.

The recurrence of formulaic cohesion and limited lexical scope suggests that many learners rely on AI for structural and lexical assistance rather than for content generation. Teaching strategies should therefore focus on rhetorical awareness to help students recognize the difference between grammatical correctness and rhetorical depth. Classroom activities might include comparative analysis of human vs AI-drafted passages to highlight variation in tone, stance, and lexical precision.

For institutions, the findings accentuate the need for transparent policies that balance integrity with innovation. Assessment design should move toward process-based evaluation, valuing idea development, drafting stages, and revision commentary alongside the final product. Writing programs can integrate short reflective annotations where students specify what kinds of tools they used (grammar checkers, paraphrasers, text generators) and justify their choices. This approach reframes AI use from a threat to integrity into an opportunity for ethical literacy.

Broader Implications for Quality Assurance and Research

At the systemic level, the evidence from this large corpus intersects with ongoing debates about quality assurance in higher education. As universities globally revise learning outcomes to include digital competencies, AI literacy is increasingly recognized as part of academic skill development. The stylistic convergence observed exemplifies the institutional challenge: guaranteeing that fluency achieved through technology does not mask deficiencies in critical thinking or writing independence.

For researchers, the methodological implication is equally significant. The present study validates that linguistic trace analysis that combining quantitative metrics (sentence-length variance, TTR) with qualitative coding (voice, cohesion, framing) can detect indirect textual shifts indicative of AI influence without relying on algorithmic detectors. This contributes to an ethically grounded framework for future studies seeking to map human-machine co-authorship in educational contexts.

The recurring textual tendencies: formulaic cohesion, polished impersonality, generic framing, and limited lexical breadth, reflect patterns consistent with AI-assisted drafting and editing. Collectively, these findings suggest that AI technologies are not simply tools of convenience but active agents shaping the linguistic identity of student writers. Moving forward, institutions must adopt approaches that both safeguard authorship and harness the pedagogical potential of AI, ensuring that students remain not only fluent writers but conscious and critical users of digital language technologies.

These findings suggest that AI-mediated writing is not a clean boundary between human and machine, but a spectrum in which language, stance, and textual identity are gradually reshaped as students interact with algorithmic systems. In this spectrum, writing becomes a shared space where human intention meets machine support, often blurring familiar markers of voice, originality, and proficiency. Identifying this interplay encourages educators to move away from approaches focused on policing AI use and toward teaching practices that lead to transparency, reflection, and rhetorical awareness. In this perspective, responsible engagement with AI becomes part of what it means to be academically literate, requiring students to explain how technology contributes to their writing while still taking ownership of the interpretive and argumentative work that remains distinctly their own.

Conclusion

This study demonstrates that AI-assisted writing leaves discernible linguistic and stylistic traces, particularly in cohesion patterns, lexical regularity, and the attenuation of voice, that reshape how undergraduate texts are constructed and interpreted. By examining a large corpus of authentic student writing, the study advances current understanding by revealing how AI mediation becomes visible within the language of the text itself, offering a text-centered alternative to perception-based surveys and unreliable detection tools. As AI becomes increasingly embedded in writing processes, the task for higher education is not merely to identify its presence but to guide students in navigating it responsibly, supporting transparency, rhetorical awareness, and the development of an independent academic voice. Future research should explore how these patterns evolve over time, how AI-mediated traces differ across disciplines and proficiency levels, and how students' reflective accounts of AI use relate to the linguistic features observed in their work. Such investigations will deepen our understanding of how technological mediation shapes writing development and will inform pedagogical frameworks that integrate AI in ways that are ethical, reflective, and educationally meaningful.

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