

A Comparative Genre Analysis of Human-Written and Ai-Generated Research Abstracts

*Puteri Zarina Megat Khalid, Haddi@Junaidi Kussin, Nurul Farehah Mohamad Uri, Aireen Aina Bahari, Khazaila Zaini, Nur Aliaa Amirah Kasuahdi

Department of English Language and Literature, Faculty of Languages and Communication Universiti Pendidikan Sultan Idris Perak, Malaysia

*Corresponding Author

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ABSTRACT

This comparative study explores the distinctive generic features between abstracts written by human authors and those generated by artificial intelligence tools through the genre analysis methods. Over-reliance on such external mechanisms and plagiarism are perennial issues that affect the global academia particularly in regards to the widespread dependence on artificial intelligence. The study compares ten research abstracts written by postgraduate master students specialising in English Language and Literature from a Malaysian public university to AI-generated abstracts produced using Chat Generative Pre-Trained Transformer 3, also known as ChatGPT. The study looks into the frequency and quality of key elements or moves such as statements of objectives, methods, results, and contextualisation to determine their recurrence patterns. Findings indicate that human-inscribed abstracts reveal a more stable and thorough presentation, highlighting contextualisation and inclusive results, while AI-generated abstracts possess clarity in statements of objectives with minimal coverage on results and contextual details. The findings in this research thus recommend for the development of an innovative method of detecting AI-generated content written by students using the genre analysis approach. It also emphasises the necessity for specialised teacher training and rigorous evaluation criteria to preserve academic integrity and overcome the limitations of using AI in academic writing.

Keywords: Genre analysis; AI-generated writings; comparative analysis; human-writers; research abstracts

INTRODUCTION

The plagiarism detection analysis of students' academic texts can be performed using various software and applications. One such example of software is the Turnitin which is an established platform to detect plagiarism committed by students in their scholarly texts by comparing the texts to the vast online database of academic sources. Correspondingly, this research adopts a genre analysis approach to compare and contrast the characteristics of both human-inscribed texts and those generated by tools of Artificial Intelligence (AI). Just as the plagiarism indicators in a text such as linguistic and semantic resemblances are identified by the Turnitin, the genre analysis method that this study employs scrutinises the generic structures and technical nuances of abstracts in final year project papers. Thus, it is crucial to distinguish the structural and linguistic patterns of texts organically produced by humans and those generated by AI.

The goal is to distinguish between structural and linguistic patterns in texts written by humans and those created by AI. Genre analysis can be used to study the intricacies of human communication, like written texts. This method is crucial to examining textual structures and conventions as it provides a systematic way in exploring how genres work in different socio-cultural settings. The current technological advancement has engendered the debate regarding the variations between human and AI-generated academic texts. Genre analysis is important in literacy education because it helps people understand discourse, which is a basic learning tool. It thus avails applied linguists a socially validated theory of language and an educational methodology obtained from research into texts and their contexts (Rakrak, 2025). Recent genre analysis

studies revealed that the levels of coherence and diversity in genres could be analysed by studying their structure and understanding the social processes related to them (Thane, 2024; Tan, 2024). These studies highlight the necessity to identify lexico-grammatical patterns and rhetorical strategies employed by students in texts. Alqudah (2024) notes that this is crucial for adopting the genre analysis approach to identify AI-generated academic texts. AI can mimic the superficial aspects of texts created by humans but not the complex rhetorical and contextual choices behind human writing. One of the ways to assess the differences between various types of academic writing is the genre analysis method. This way, there is no need to determine whether the students employ AI assistance and focus on what is really important. It is important for any author to learn them in order to be proficient in language and critical literacy techniques. The present study aims to broaden previous investigations by analysing the genre features of research abstracts authored by humans and AI. While the findings from our focused, small-scale dataset offer valuable initial insights, we frame this work as a pilot study that highlights the need for larger-scale validation and provides a transparent methodological framework for future research in this domain.

Theoretical underpinnings

Understanding how academic writing functions more broadly is crucial for genre analysis. The method was first proposed by Swales (1990). He demonstrated that the forms of written and spoken language, which exist to fulfil certain functions of communication within a society, are intentional. This highlights the importance of genre in academic writing. The rhetorical building blocks used to label texts for genre categorisation are called “moves” and “steps” (Swales, 1990). In the introductions of research articles, authors generally use several writing steps such as establishing a research territory, identifying a niche, and occupying the niche. To have an academic discussion, you must be aware of the discourse structure. Swales’ method is a helpful way to teach genre-specific writing. Additionally, the method provides a solid basis for identifying AI-generated texts that imitate human writing structure but lack its rhetorical and social components (Nanola et al., 2025). This highlights the need to integrate genre-based pedagogy into the language curriculum as a way of promoting critical literacy (Zhou 2025).

Bhatia (1993) extended genre analysis to professional and academic genres, such as research abstracts and articles, pointing out that disciplinary practices and technologies of communication are dynamic, thereby continuously evolving. His work enhanced understanding that academic writing is both structured and flexible. The underpinning theories are reflected in the Figure 1 below. Genre analysis has been extensively used for the evaluation of research abstracts. Hyland (2000) showed that writing an abstract follows a move-based model: purpose, method, result, and conclusion. This format makes abstracts short but still useful, so readers can quickly understand the main point of a study.

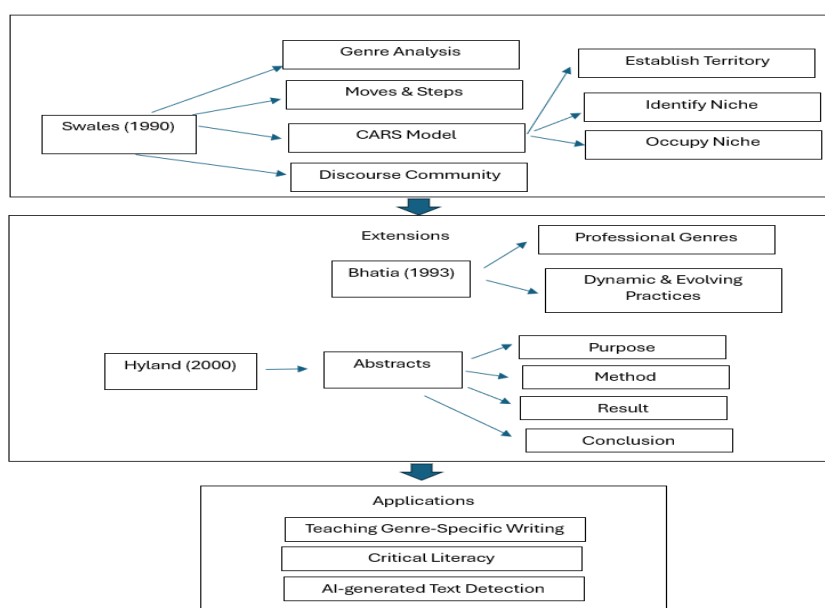


Figure 1: Foundational theories of Genre Analysis in this study

REVIEW OF RELATED LITERATURE

Moves and Steps in Different Types of Scholarly Writing

Swales (1990) defined "moves" as the communicative actions utilised by writers to achieve the goals of a genre. In the introductions of research articles, common strategies include defining the research area, assessing prior studies, and identifying a gap. Bhatia (1993) further clarified this concept by introducing "steps," which are smaller components within moves that support the overall communicative goal. In abstracts, typical moves involve providing background information, stating the research objective, outlining the methodology, reporting findings, and drawing conclusions. Recurring move structures are evident across academic genres. A widely recognised example is the IMRaD format (Introduction, Methods, Results, Discussion), which organises many research articles. Each section serves a specific role: the Introduction presents the problem, Methods describe the procedures, Results report findings, and Discussion interprets those findings and their implications (Alqudah, 2024). The genre analysis via its move identification processes offers a rigorous investigation of how scholarly texts are structured to serve the intended their communicative purposes. With a clear understanding of these structures, scholars and researchers can thus be better equipped to distinguish the texts produced by humans from those generated by AI.

Comparison between human-written texts and AI-generated ones

Several studies have been conducted on distinguishing the writings produced by humans and AI tools. Frangieh and Abdallah (2024) identified the essays generated by ChatGPT displayed more sophisticated vocabulary, more succinct sentences, and a professional, objective writing style. They also found that texts written by humans were far richer in terms of emotions, authenticity, and personal references. There was also more profound diversity in ideas and stylistics in the students' writing, whereas the texts generated by ChatGPT exhibited uniformity with formulaic expressions. These findings are corroborated by Eğin et al. (2025) who performed a comparative analysis of human-written materials and texts generated by ChatGPT, BingAI, and Gemini. Their study revealed that human authors produced longer texts with more complex sentence structures and richer vocabulary. They also found that the AI outputs, on the contrary, depended on fillers, repetitive stereotypical expressions, and structured but reduced linguistic subtlety. Verbosity and repetitions were inherent in the texts produced by Gemini which assisted in convenience of detection. ChatGPT's outputs, on the other hand, bore close resemblance to human-written texts, posing acute difficulties to distinguish.

Studies by Hakam et al. (2024) and Muñoz-Ortiz et al. (2024) examine the differences between texts generated using the AI tools and those authored by humans from varying perspectives. Hakam et al. highlight that AI outputs are normally lacking in depth, critical analysis, and originality despite the tools being able to generate texts which coherent and structured. The AI materials were also found to rely more on surface-level generalisations than practical and substantial arguments. On the contrary, Muñoz-Ortiz et al. adopt a quantitative linguistic approach to the textual analysis via comparison of human-written news articles to the texts from multiple large language models. Their findings indicate that the vocabulary and sentence length in the texts produced by human authors are more varied with varying grammatical patterns, and contain greater emotional elements. AI-generated texts, on the other hand, are more objective, patented by heavier use of figures and symbols. Despite their apparent diverge views, both research converge on the perspective that AI-generated writing is generally devoid of complexity, variability, and analytical nuances of human authors' expressions. This reinforces the notion that AI merely serves as a complement and not a replacement for human writers.

All in all, these studies have highlighted the fact that human authorship has not lost its originality and sophistication despite the clarity of the outputs by the AI tools. This underscores the need for the development of effective detection tools in order to sustain academic integrity and fidelity.

The Drawbacks of Using AI for Academic Genre Creations

Numerous significant developments have been accomplished using AI in natural language processing and text creation. One such tool is GPT-3, built by OpenAI, which is able to generate interdisciplinary texts with

coherence and contextual relevance (Barbosa, 2024). Nevertheless, the incorporation of AI in academic text creations poses numerous setbacks, specifically with regard to regulating academic integrity. In addition, challenges are also inherent in ensuring the authenticity of academic genres.

Among the major drawbacks is the problems in differentiating human-written texts from AI-generated ones. Federiv et al. (2024) highlighted that AI-developed texts frequently display particular features, namely redundant phrasing and insufficient contextual depth. The generic features are formed by the algorithms employed in the training of AI models. Coherence and clarity are given more weight in the features than comprehension and originality. The texts generated by ChatGPT-3 are grounded on patterns acquired from a wide array of training data. Although such a tool can generate texts that replicate human writing, it fails to engage in great depth with the content or even incorporate previous research meaningfully (Amirjalili et al., 2024; Maurya & Maurya, 2024). Because AI tools often provide limited contextualisation and lack critical engagement with the literature, producing rigorous academic content using AI remains a challenge. Another long-standing concern is the issue of authorship and originality as human writers increasingly rely on machines (Mazzi, 2024), the boundary between human and AI-written texts becomes blurred. This shift raises ethical questions about the credibility of AI-generated academic work and its implications for the trustworthiness of scholarly publications.

It is even harder to use AI in research writing because we need reliable ways for discovering information. Ghiurău and Popescu (2024) underscore the necessity of improving instruments capable of detecting AI-generated content by concentrating on recurring structures, superficial analysis, and various linguistic indicators. A better technique would be to combine automatic text assessments and expert ratings (Verhulsdonck et al., 2024). Algorithms use machine learning and NLP to rapidly analyse large amounts of text data. The machines detect regular patterns, style problems, and repetitions that reflect AI-written content (Arshed et al., 2024). Nevertheless, those machines encounter challenges in comprehending rhetorical strategies and genre conventions that are critical for academic writing coherence (Ramazani et al., 2025). Such an issue is best addressed by human raters as they have the capacity to detect subtleties and other inconspicuous elements in academic writings, particularly those produced by human authors. This shows the necessity to incorporate genre analysis and critical literacy into language learning. Such an approach will ensure that academic writing is not only precise but also contextually and culturally appropriate.

The present research aims to address the issue of over-reliance on AI gadgets for writing by analysing ways of ensuring that the AI-generated content meets the rigorous academic writing standards. The algorithmic setup employ machine learning and natural language processing (NLP) for swift identification of large text collections. They are able to detect regularities in patterns, style problems, and repetitions that may indicate AI-formulated materials (Arshed et al., 2024). For efficient and effective algorithmic functions that capitalise on machine learning and NLP, human writers should be trained to master the academic rules and regulations, genre rules and ways to improve their writing beyond basic issues pertaining to texts. Academic writers often have specific knowledge of rhetorical methods, reasons for selections, and the appropriateness of the texts within the relevant disciplines (Zhang, 2023). This understanding is helpful in ascertaining if a text merely replicates academic writing or whether it genuinely adds value to the subject matter. Detection is made easier when embedded with human experience. With the inclusion of human knowledge, the AI content is identified not only through variations of styles but through better content engagement and clear composition skills (Mobilio, 2024).

The combined execution of text analysis methods and human judgment is a blended approach for achieving academic integrity (Gupta, 2024). Computerised systems are installed with the scaled capacity for speedy operations to scrutinise vast quantities of text and provide annotated markers that flag potentially AI-generated materials. This function facilitates human writers to perform a thorough examination of the marked texts in making informed conclusions. This process is further guided by the author's own knowledge and mastery of the particular academic genres and the related rhetorical strategies.

Human feedback now has the ability to improvise automated models with greater accuracy as the detection of AI-generated texts is enabled through this blended method. This leads to an enhanced AI-powered text generation where investment in both automated and human authors yields a more accurate and reliable

detection process which ensures the authenticity and integrity of scholarly writings (Aburass & Abu Rumman, 2024).

Genre analysis is a method to help scholars understand how academic writing is pieced together through strict adherence to the corresponding rules. This shows the importance of identifying moves and steps in the writing of scholarly themes. Nevertheless, several setbacks have also been discovered in the utilisation of AI in scholarly writing. Certain pertinent threats like originality, creativity, and effective detection of AI intervention must be clearly addressed by the users. For a more efficient and effective handling of these issues, a comprehensive strategy encompassing enhanced detection methods and a better understanding of the various scholarly genres is thus crucial. This paper thus attempts to analyse both AI and human texts and suggest solutions to deal with the possible problems with AI-generated materials.

METHODOLOGY

This study adopted a comparative genre analysis approach, utilizing the foundational models of Swales (1990) and Bhatia (1993). Given the exploratory nature of this inquiry and the detailed, qualitative analysis required, a pilot study was conducted with a focused dataset. The primary dataset consisted of ten research abstracts written by postgraduate master's students specializing in English Language and Literature from a Malaysian public university. These abstracts, covering diverse topics in language, literature, and education, provided a rich, authentic corpus of human-authored academic writing.

For the AI-generated corpus, Chat Generative Pre-Trained Transformer 3 (ChatGPT), specifically the gpt-3.5-turbo version (May 2024 snapshot), was utilised. To ensure a direct comparison, the AI was prompted to generate abstracts based on the same thematic areas as the human-written abstracts. The specific prompt used was: "Write a research abstract for a master's thesis in [Topic Area, e.g., 'applied linguistics']." This prompt was chosen for its simplicity and to mimic a likely student input, allowing the AI's default structuring tendencies to emerge without heavy steering.

The analytical framework for the first phase of the study was Melliti's (2016) Create a Research Letter (CARL) Introduction Model. This model was selected for its structured approach to identifying moves and steps, which align well with the succinct nature of research abstracts. A detailed codebook (see Appendix A) was developed based on the CARL model, defining each move (e.g., Purpose of Study, Methodology, Results) with clear linguistic criteria and examples.

Coding Procedure and Reliability

Two trained coders, both applied linguistics researchers, independently analysed all twenty abstracts (10 human, 10 AI). The coding process involved segmenting each abstract into sentences or T-units and classifying them according to the moves defined in the codebook. Following the initial independent coding, an inter-rater reliability analysis was performed using Cohen's Kappa, which yielded a score of $\kappa = 0.85$, indicating a high level of agreement. All discrepancies were discussed and resolved through consensus, ensuring the final frequency counts were consistent and reliable.

Data collection procedure

In this study, ten mini-memoir abstracts that were written between December 2024 and April 2025 as part of an in-class activity were selected for analysis. The texts were written by postgraduate master students majoring in English Language and Literature at a public university in Malaysia covering a wide range of topics on language, literature, and discourse. Four abstracts focused on language, three on literature and three on discourse. An advanced tool, ChatGPT3, was used, for the creation of another set of mini-memoir abstracts for similar thematic areas, while maintaining a thorough comparison between the two sets. The researcher typed the themes of the mini-memoirs into the ChatGPT chat bar and requested it to produce an abstract for each.

Analysis of data

Next, each abstract was carefully read, whether it was authored by a person or an AI. Due to the complexities associated with genre analysis, this method was preferred over automated ones. Human analysts, on the other hand, possess the cognitive ability to distinguish the subtle meanings underlying each statement (shown by the letter S in Table 1 below). The breaking down of the components of the abstracts was done with great detail for the purpose of determining the underlying generic elements, employing Melliti's (2016) framework for Creating a Research Letter (CARL) Introduction Model.

Table 1 Melliti's Create a Research Letter Model (CARL Model) (2016)

Introduction	
Introduction Phase (IP): 3 S	Background Information (BI)* 1 S
	Previous Research (PR)** 1 S
	Previous Research/Background Information (PR/BI)* 1 S
Contextualisation Phase (CP): 5 S	Identification of Gap (IG)* 1 S
	Purpose of Study (PS)* 1S
	Rationale for Study (RS)** 1 S
	Methodology (ME)** 1S
	Previous Research/Identification of Gap (PR/IG)** 1 S
Findings Phase (FP): 4 S	Results (R)* 2 S
	Conclusion (C)* 1 S
	Results/Conclusion (R/C)** 1 S

*note: The letter 'S' refers to 'Sentence'

The choice of Melliti's (2016) Research Letter Introduction Model for this study was intentional and strategically aligned with the attributes of the mini-memoir genre. The justification for this selection is based on the intrinsic similarities between the research letter and the mini-memoir, as both function as succinct representations of their corresponding extended versions within academia. The research letter is a shorter version of a regular research article that includes all the important parts of a scholarly inquiry in a small space. In the same way, the mini-memoir, which is a short version of the master thesis, captures the main points of the research project in a shorter form while retaining its academic nuances. Both types of writing are short, which is a good way to share academic ideas without losing the essence of scholarly research. The study used a model customised for research letters, which is in line with established academic norms to ensure the consistency and comparability of the methods to other scholarly frameworks.

RESULTS AND DISCUSSION

The table provided below identifies the recurrence of keys in the AI generated vs. human written abstracts. Table 2 below illustrates that in the AI-generated set of abstracts, "Purpose of Study" (PS) is the predominant text function, comprising almost fifty percent of the references (24.1%). This elevated percentage signifies a robust focus on explicitly describing the research's objective. The presence of PS in these abstracts indicates that the principal purpose is to ensure that readers promptly comprehend the research's aims. In contrast, only 11.8% of the human-generated abstracts in the collection contain PS. It implies that asserting the purpose is

essential but it is not the only thing that matters. The fact that there is less focus on PS in the human-written set could suggest that the writer is taking a more balanced approach to writing abstracts, giving more weight to components like methodology, results, and previous research. The "Methodology" (ME) section remains constant in both datasets. It appears more frequently in the human-written dataset (20%) than in the AI-generated set (17.2 %). The consistency shows how important it is to clearly explain the methodological approach in both AI-generated and human-written abstracts. The small increase in the human-written set may mean that more attention is being paid to the research process and the methods used, which could indicate that the approach is thorough or particularly methodical.

Table 2 Frequency count of key recurrence in Human-written vs. AI-developed abstracts

Text Function	Examples of AI generated sentences	AI Count	AI Percentage	Human Count	Human Percentage
Background Information (BI)	"The historical trajectory of English in Asia, stemming from diverse colonial encounters and evolving through complex processes of indigenization, adaptation, and multilingual contact, necessitates a comprehensive diachronic analysis to understand its contemporary forms and functions across the region."	3	10%	6	11.8%
Previous Research (PR)	"Studies indicate that women utilise more reduced speech acts than men."	3	10%	8	15.7%
Identification of Gap (IG)	"There is a dearth of research on how young learners master grammatical competence in bilingual settings."	6	20.7%	6	11.8%
Purpose of Study (PS)	"This study aims to investigate how gender representation is expressed in local novels."	7	24.1%	6	11.8%
Methodology (ME)	"Employing a qualitative approach, this study utilised semi-structured interviews to explore student's experiences through thematic analysis."	5	17.2%	10	20%
Results (R)	"Allegory is a useful tool to expound on abstract themes in literary works."	0	0%	9	17.6%
Conclusion (C)	"This study shows a positive relationship between linguistic competency and linguistic performance."	5	17.2%	6	11.8%
Results/ Conclusion	"The findings indicate that discourse markers improve	0	0%	2	3.7%

(R/C)	narrative cohesion, thereby affirming their significant role in enhancing reader comprehension.”				
Hypothesis (H)	“There is a relationship between linguistic competence and linguistic performance.”	0	0%	3	5.6%

Earlier studies show that there is an immense distinction between the two sets. There are 15.7% of instances of PR in the human-written collection, but only 10% in the AI-generated set. This substantial variation demonstrates that the human-written set emphasises on placing the current study in the context of other research. The contextualisation is essential for exhibiting how relevant and original the research is. Its higher frequency in the human-written dataset could imply that the literature review elements are more fully integrated. To assess the statistical significance of the observed frequency differences between human and AI-generated abstracts, a Fisher's Exact Test was performed due to the small sample size. The test revealed a statistically significant difference in the distribution of moves between the two groups ($p < .05$). Specifically, the over-representation of "Purpose of Study" (PS) in AI abstracts and the under-representation of "Results" (R) were key drivers of this significance. This statistical test strengthens the confidence in our findings, suggesting that these divergent patterns are not due to random chance but reflect fundamental differences in compositional focus.

There are about the same number of times that both sets mention "Background Information" (BI) and "Identification of Gap" (IG). In the dataset made by AI, BI and IG both display 10% and 20.7%, but in the dataset written by humans, BI and IG appeared 11.8% each. This means that both groups still need to provide context and highlight the research gap. The small increase in BI in the human-written set may mean that the subject matter was presented in more detail. The IG levels, on the other hand, suggest that the group was focused on finding and fixing gaps in their current understanding. The higher proportion of "Identifying Gaps" (IG) in AI-generated abstracts suggests that the system is designed to make research gaps stand out more clearly. Such a clarity is advantageous to novice writers as articulating gaps in the literature is often one of the most commonly challenging aspects of abstract writing. Generally, in this context, AI devices may be considered a helpful assistant to users for identification of research gaps. Therefore, these machines have the potential to be an invaluable resource for research activities. However, along the same breadth, the AI tools pose a significant drawback to novice users. The users' over-reliance on AI may impact their own writing abilities, especially in areas where the beginner users have the least capability.

On the contrary, the abstracts written by human authors in this research contain a higher percentage of coverage for Results (17.6%) and Conclusions (11.8%), meanwhile the AI-written abstracts lack a specific section on Results and cover only 17.2% of Conclusions. This suggests that the human-written abstracts dedicate a section to discussing the findings of the study with explicit emphasis on the outcomes of the research. Effective statements of significance and contributions of a study necessitate an accuracy in the composition of the research. In the dataset produced by human authors, a blended section comprising Results/Conclusions (3.7%) and Hypotheses (5.6%) was found, but these characteristics did not exist in AI-written data. This indicates that there is a wider array of rhetorical functions in the abstracts produced by human authors. Additionally, the abstracts too are more nuanced and diverse. This practice is termed as "a tendency to innovate" by Bhatia (1993). Thus, it is not uncommon in academic discourse communities that when reporting research results scholars try out different ways of doing things, like stating hypotheses explicitly or combining results and conclusions. The presence of these features indicates that human writers employ various techniques for enhancing the communication aspects of their study. The analysis of patterns in abstracts written by both humans and AI shows that they follow the rules of writing academic abstracts. The genre analysis reveals that both groups generally follow the expected structure of research articles (background information, purpose, gap, method, results), although they may emphasise different aspects. This is in line with the conclusion that academic abstracts are a very conventional genre targeted at effective and precise transmission of critical information to the academic community.

A significant variation lies in the way PSs are treated. AI abstracts tend to focus more on the study's purpose, whereas human abstracts distribute emphasis across various aspects. The AI appears to place more emphasis on the clarity of an article's goals, while humans balance that aspect with the context, method, and results. AI-written abstracts focus more on "what the study is about," whereas human-written abstracts include both "what the study is" and "what it found." It can be observed that both human and AI-generated abstracts share a similar structure but place emphasis on different sections of the rhetorical aspect. Genre analysis helps identify these distinct features, enabling educators and researchers to understand that AI-generated texts, while rule-based, lack the flexibility and nuance inherent in human writing. These differences not only demonstrate the equality of academic rigor but also highlight the distinct approaches through which human and AI critics comprehend the same genre. The findings have important implications for identifying AI-generated writing in students' work. Educators and detection devices will better differentiate between human and AI authors' structural and rhetorical strategies to find plagiarised texts. According to this study, the signs that are considered the most trustworthy are:

- **Increased Frequency of Statements of Purpose:** an uncommon prevalence of "Purpose of Study" statements may indicate AI-generated content, as AI often emphasizes clear and stated aims.
- **Incomplete Results and Conclusions:** AI-generated articles fall short of complete results and conclusions that elicit the purpose and methodology of the research rather than the research itself.
- **Insufficient Contextualisation:** AI-generated information can suffer from a lack of complete contextualisation that is often found in human-generated abstracts, particularly with the incorporation of existing research.

Discourse-Level Analysis of the Abstracts

This research contrasts students' abstracts and AI-generated abstracts on the basis of two significant dimensions: the degree of complexity in language and how framed the discourse is.

Language Complexity

We measured the complexity of the language in terms of the quantity of detail and technicality in every abstract (Godwin-Jones, 2025). This involved how specialised words, discipline terminology, and sentence structure were used. An examination was also carried on identifying the functionality of technical terms in the addition of depth to the content without making it challenging for the intended audience to understand. This method showed how word and sentence-level choices could make an abstract more accurate and understandable. A chi-square test of independence confirmed that the use of discipline-specific terminology was significantly higher in human-written abstracts ($\chi^2(1, N = 20) = 6.67, p < .01$), reinforcing the qualitative observation of greater lexical complexity.

Organising Discourse

Analysis of discourse organisation focused on the organisation and presentation of content within abstracts (Botchwey & Owusu, 2024). The following characteristics were analysed: move structures, ideational ordering of ideas, and theoretical presentation-empirical data-methodological description relationships. An observation was also performed to determine whether or not the abstracts referred to practical application, significant findings, or recommendations. Organisational systematicity between abstracts was realised through application of the similar set of analytical criteria.

Table 3 AI-generated vs Human-written abstracts

Set	Aspect	AI generated	Human written
S1	Language complexity	Clearer and more general descriptions of methods and objectives	Employs discipline-specific terminologies

	Discourse organisation	Emphasises objectives, methodologies, and implications, with reduced focus on theoretical frameworks	Methodology and outcomes are presented in details with specific references provided
S2	Language Complexity	The approach is straightforward and emphasises tangible consequences alongside empirical studies	Comprehensive definitions and their implications; intricate sentence structures employed
	Discourse organisation	Structured around empirical studies and practical outcomes with reduced focus on definitions	Organised into definitions, methodologies, results, and implications
S3	Language Complexity	Language is generally formal and structured with consistency in grammar and clarity in expressions	Language laced with informality and fragments alongside irregularities in grammar and overall structures
	Discourse organisation	Structured with distinct sections addressing research methods, findings, and implications.	Disorganised discourse structures with sentence fragments; lacks clarity in focus and organisation
S4	Language Complexity	Concise and direct, yet theoretical in nature; emphasises practical implications	Intricate and theoretical with thorough discussions of various factors
	Discourse organisation	Emphasis given to empirical findings and implications; structured around particular case study and context	Thorough investigation of hypotheses and variables, encompassing a range of research techniques and ramifications
S5	Language Complexity	Clarity of expressions and focus on empirical elements with less attention given to technical particulars	Comprehensive and specialised terminologies encompassing precise definitions and theoretical elucidations
	Discourse organisation	Emphasis given to empirical strategies and results which were structured around case studies and implications	Thorough structuring includes an in-depth examination of theoretical frameworks and methodologies
S6	Language Complexity	Concise and pragmatic; emphasises execution and practical application of the subject matter	In-depth examination of the subject; intricate syntactic constructions
	Discourse organisation	Structured around empirical findings and recommendations with less focus on theoretical underpinnings	Organised around theoretical background, methodology, and analysis
S7	Language Complexity	Concise and practical; emphasises a particular case study and empirical evidence	Emphasised theories with thorough references and intricate explanations
	Discourse organisation	Organised around practical research and findings related to specific case studies	Comprehensive analysis of the study preceded by theoretical framework
S8	Language Complexity	Theoretical yet orientated towards practical applications; succinct and lucid reporting	Intricate and abstract; comprehensive examination of the subject

	Discourse organisation	Organised around empirical analysis of particular case study and theoretical ramifications	Comprehensive examination incorporating theoretical and narrative components.
S9	Language Complexity	Expressions are more direct with emphasis on particular drawbacks and recommendations	Thorough details of limitations and hypotheses with diverse complexity
	Discourse organisation	Structured around particular findings and recommendations with clarity in organisation	Comprehensive investigation of drawbacks with diverse organizational structure
S10	Language Complexity	Concentrated on the pragmatic dimensions of emerging technology using precise, empirical terminology.	In-depth examination of emerging technology; incorporates particular citations and intricate language structures.
	Discourse organisation	Organised around case studies and real-world examples, with little emphasis on theoretical foundations.	A complete analysis that covers both theory and practice

Comparisons between the two datasets

When the two datasets were compared, it became evident that they were very different in terms of language and discourse organisation. The analysis indicated that human authors and the AI machines employed different strategies for information and expressions of thoughts. Several notable differences were detected in linguistic sophistication and discourse structures between AI-generated abstracts and human-written ones. The findings offered insights into the varying practice of academic writing by both human authors and AI tools. A thorough examination into the degree of complexity of technicality of the research abstracts involved the analysis of how the technical, discipline-specific words and sentence structures were used (Godwin-Jones, 2025). The evaluation of the use of technical terms by the authors was performed to establish the depth of the abstracts without compromising its clarity. The technique demonstrated how the author's choice of word and sentence structure impacted the accuracy and clarity of the intended meaning.

The structure and presentation of the content in an abstract can be studied by examining its discourse organisation. The examination was performed by analysing the move structure and flow as well as the balance between theory framing, empirical argumentation, and methodological explication (Botchwey & Owusu, 2024). It was also important to determine if the abstracts mentioned the implications, key findings, and recommendations. The systematic analysis of content organisation in the abstracts was guaranteed by applying the same criteria. The analysis focused on the strategies adopted by human writers and AI tools in the writing of research abstracts and how linguistic choices and structural organisation affect clarity and coherence. It was found that the differences between the two datasets in terms of linguistic complexity and discourse structure were apparent.

Language Intricacy

Academic abstracts written by human writers tend to display a higher quality of language command. As illustrated in Table 3, the examples taken from the human authors indicate that they use the exact wording together with technical terms and phrases as well as discipline-specific jargons. The use of such structures allows the authors to provide accurate explanations with greater degree of engagement with the ideas presented in the abstract. This system, however, presents privileges for human authors with advanced knowledge but it poses challenges for those with little understanding. These findings support Sardinha's (2024) claims that AI systems face challenges in understanding or interpreting complex content.

AI-generated ones use simple words and sentences to generally describe the methods and goals. While that makes things easier, what they produce is not on the same level as human work. AI also favours clarity and conciseness, which make reading about complex topics easier but less informative (Zheng, 2024). One of the major criticisms is that AI-generated texts are general and vague. Academic texts that are excessively simple and do not apply any scientific terminology might have been generated by software.

Organisation of Discourse

Human abstracts exhibit a precise and highly organized discourse structure. They talk about things like methodology, findings, implications and theoretical discussions. This well-organised study makes it possible to look at the subject matter from different angles and present qualitative conclusions in a balanced manner. AI abstract is more focused on the research goals, methods, and practical results than the human one. AI abstracts are easier to understand because they predominantly discuss empirical study results and applications. However, they may not exhibit the same level of analytical depth and theoretical rigor as human-generated academic papers. The structure and organization of the AI-generated text are very basic, which affects the overall clarity and coherence of the paper. This indicates that the discourse structure could be used as a provenance marker. AI-generated content is quite basic and practical without immersion into theoretical and methodological issues.

Towards Automated Detection: Operationalizing Genre Features

The distinct genre features identified in this study have practical implications for developing AI-detection systems. The move-based patterns can be translated into feature sets for machine learning classifiers. For instance:

- Lexical Features: A lower frequency of discipline-specific jargon and technical terms could serve as an indicator.
- Syntactic Features: Lower sentence complexity scores (e.g., measured via parse tree depth) may flag AI-generated t
- ext.
- Move-Structure Features: A classifier could be trained to identify an imbalance in move frequencies, such as a high PS-to-R ratio or a complete absence of a Results section, which was a hallmark of the AI-generated abstracts in this study.

While current automated detectors often rely on perplexity and burstiness metrics, integrating explicit genre and rhetorical features could enhance their accuracy, especially against models fine-tuned to evade statistical detection. Our findings suggest that a hybrid system, combining statistical analysis with rule-based checks for rhetorical structure completeness, could be a promising avenue for future development.

CONCLUSION

The study employed genre analysis to identify distinctive features of research abstracts generated by humans and AI. While the pilot-scale dataset offers valuable insights, we acknowledge that the small, single-site sample limits the generalisability of the findings. The exclusive use of ChatGPT-3.5 also means the results may not be fully representative of other, more advanced LLMs. Future studies should employ larger, multi-institutional datasets and include a wider array of LLMs (e.g., GPT-4, Gemini, Claude) to validate and extend these findings.

This study underscores the necessity of developing specialised methods for detecting AI-generated writing. The move-analysis approach, complemented by statistical validation, provides a transparent and pedagogically useful framework. For educators, this translates into the need for targeted training to recognize not just stylistic quirks, but structural and rhetorical shortcomings in student submissions. For the research community, it highlights the potential of integrating genre-based features into the next generation of AI-detection tools.

Ethical considerations

- The study was conducted with the informed consent from the participants. The anonymity of the students who participated in this study was guaranteed as their identities and personal details were not disclosed in this paper. In addition, the confidentiality of their writing outcomes was also guaranteed to only be shared in this paper. The students were also allowed to withdraw from the study should they feel like doing so prior to the start of or during the research.
- This study was conducted after obtaining the research ethics approval from Universiti Pendidikan Sultan Idris [UPSIPPPI/PYK/ETIKA(M)/Jld.19(97)].
- We declare that there are no potential conflicts of interest with respect to this research, authorship, or publication of this article.

Data availability

The datasets generated and analysed during this pilot study are not publicly available to protect the confidentiality and academic integrity of the student participants, as the human-written materials are original coursework that could reveal identities and writing styles. The AI-generated data are also withheld to prevent their potential misuse as templates for academic work. However, to ensure the transparency and reproducibility of our analysis, anonymised exemplars of one human-written and one AI-generated abstract, along with the full analytical codebook (Appendix A), are provided in the supplementary materials. The complete dataset is securely stored in the institutional repository and may be made available to qualified researchers upon reasonable request, subject to ethical approval from Universiti Pendidikan Sultan Idris.

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Appendix A: Analytical Codebook for Move Analysis

Example Entry:

- **Move: Purpose of Study (PS)**
- **Definition:** A sentence or clause that explicitly states the aim, objective, or research question of the study.
- **Linguistic Cues:** "This study aims to...", "The purpose of this research is...", "We investigate..."
- **Example (AI):** "This study aims to investigate how gender representation is expressed in local novels."
- **Example (Human):** "This paper seeks to explore the interplay between post-colonial theory and modern Malaysian poetry."

Appendix B: Anonymised Exemplars with Move Annotation

Exemplar 1: Human-Written Abstract (Anonymised)

Title: Navigating Identity: Code-Switching in Multilingual Professional Environments in Malaysia

[BI] The linguistic landscape of Malaysia is inherently multilingual, presenting a complex environment for professional communication. [PR] Previous sociolinguistic research has established code-switching as a common phenomenon, yet its strategic functions in specific professional domains remain underexplored. [IG] There is a scarcity of research focusing on the intentionality and perceived efficacy of code-switching among young professionals. [PS] This study aims to investigate the strategic functions and perceived effectiveness of Malay-English code-switching in business meetings. [ME] Employing a qualitative case study design, data were collected through semi-structured interviews with eight marketing executives and through non-participant observation of five team meetings, which were subsequently analysed using thematic analysis. [R] The findings reveal that participants strategically employ code-switching to build rapport, assert authority, and clarify complex concepts. [R/C] This suggests that code-switching is not merely a linguistic reflex but a nuanced communicative strategy that enhances professional interaction and operational efficiency. [C] The study concludes that recognizing the strategic value of code-switching can inform more effective, culturally-attuned communication training programmes in multinational corporations.

Exemplar 2: AI-Generated Abstract (Anonymised)

Title: An Analysis of Gender Representation in Contemporary Young Adult Fiction

[PS] This study aims to investigate the portrayal of gender roles and stereotypes in contemporary young adult fiction. [IG] While gender representation has been a topic of scholarly interest, a focused analysis on recent publications from the past five years is lacking. [BI] Young adult literature serves as a significant socializing agent for adolescents, shaping their perceptions of societal norms. [ME] Utilizing a qualitative content analysis approach, a purposive sample of ten bestselling young adult novels published between 2020 and 2024 was systematically examined. [C] The analysis indicates that while there is a move towards more progressive representations, traditional gender stereotypes persist in character archetypes and narrative outcomes. [C] This study underscores the need for continued critical engagement with literary content to promote gender equity among young readers.