



Taxis and Logico-semantic Relations in AI-Generated Vs. Human-Written Argumentative Essays: A Comparative Study

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Publication details:

Received: April 10, 2023

Accepted: May 28, 2023

Published: June 30, 2023

Abstract

Recently, Artificial intelligence (AI) has marked a drastic, potential and tremendous impact in different fields of human life and academia is one of them. Open AI's ChatGPT is one of the emerging and remarkable AI-Language model tools that respond to the form of comprehensive text according to the requirements of the users. This research aims to find out the similarity and differences between AI-Generated argumentative essays and Humanly Composed argumentative essays on the bases of their logical meta-functions. For this purpose, the System of Clause Complexes consisting of taxis and logico-semantic relations (Halliday & Matthiessen, 2014) has been employed as the theoretical framework. Furthermore, 10 ChatGPT-generated, 10 EN users-written and 10 ESL learners-written argumentative essays are collected and annotated by using the UAM tool. The finding reveals major differences; AI-generated AEs carry a higher percentage of clause complexes, and paratactic and positive additives as compared to human-written AEs. Moreover, variation, alternation, and conditional relations are non-existent in AI-generated AEs, however, humans construct these relations during argumentation. The finding provides insight to AI-creator about the limitation and advancements regarding it as well as to English language teachers and learners.

Keywords: AI, Human Writings, Taxis and Logico-semantic Relations, SFL, Argumentative Essays

1. Introduction

1.1 Artificial Intelligence and Natural Language Process

AI, natural language processing Machine learning appeared as a revolutionized field that marked a significant influence on human life and its industries, application and activities (Wamba et al. 2021). Several scholars were predicting human-like reasoning judgements and communications by AI agents for decades (Russell & Norving, 2010). Although, the aspect of communication in the form of conversation, as a consequential complex has appeared, the area of decision marking is still under development (Agrawal et al., 2017; Ingrams et al., 2022; Hancock et al., 2020).

ML is an essential unit of AI that encompasses the creation and development of computational models' algorithms and theories for learning processes. It empowers machines to learn from experience without explicitly programming (Chowdhary, 2020; Mahesh, 2020). Similarly, NLP is marked as a key factor in this AI design that enables the machine to communicate naturally like a human conversation (Radford et al., 2018). Intelligent agents are identified software capable to do autonomous actions and decision-making by observing and utilizing the environmental factor, human input and internal knowledge. Chatbots also referred to as conversational artificial intelligent bots used NLP that can design human-like text and voice conversations in response (Khanna et al., 2015). They are collecting growing popularity due to their wide-ranging application in different areas such as customer service, academia, health and personal support (Brandtzaeg & Følstad, 2017; Nagarhalli et al., 2020). ChatGPT is one of them that showcases its potential application in academia. That is why, current research has aim to explore the potential similarities and differences between human and AI-generated academic writing (Argumentative Essays) at the clause level (Taxis and Logic-semantic relations).

1.2 ChatGPT

ChatGPT has been recognized as a disruptive innovation that transforms the landscape of academic and scholarly discourse (Arif et al., 2022). It is a natural language processing tool that offers and provides automated assistance in generating scholarly manuscripts such as essays etc. This chatbot is an innovative revolutionized and significant product of the OpenAI research laboratory established in 2015 along with the highly advanced language model GPT-3. It is trained by employing a large corpus of text data and utilizes the NLP to respond according to the users' needs and requirements (OpenAI, 2022; Zhuo, 2023; Ray, 2023). Said laboratory has garnered substantial backing from notable figures, including founding benefactor Elon Musk and the Microsoft Corporation they made a billion-dollar investment to get exclusive access to certain OpenAI products (Brockman et al., 2016). This support has propelled the laboratory's AI technology development forward at a rapid pace and now we are observing using and facing its outcomes. (Devlin et al., 2018).

The developmental process of ChatGPT carries a series of milestones and improvements such as:

- 1) The advent of Transformer Architecture. It facilitated the development of language models (Castella et al., 2023).
- 2) The Development and Availability of the GPT series. It demonstrated the capabilities of the AI language model in diverse applications like text generation, and translation summarization (Beerbaum, 2023).
- 3) The Introduction and Access of ChatGPT. It is based on the achievements of its forerunners by enhancing accuracy, contextual comprehension, and adaptability (Sallam, 2023).



The present study used the ChatGPT (AI) generated argumentative essays to do a comparative study with humanly produced argumentative essays.

1.3 System of Clause Complexes

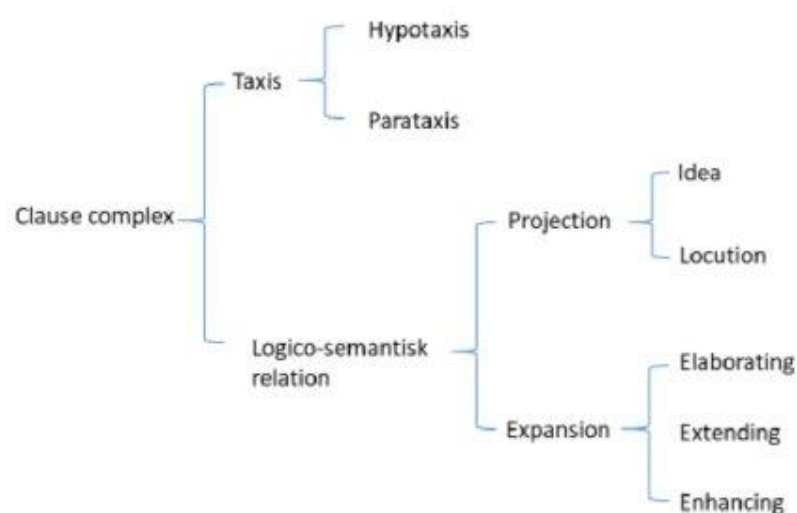
Language is context bounded through which participants, communities and people try to communicate with each other. They can share their intended meaning and understanding if they easily interpret the text, context, or pattern of a language. According to Brown and Yule (1983), text analysis provides the analysis of language. During this analysis, it is considered that the use of language is always influenced by social context, cultural context, and ideology of society.

Text is found in two forms spoken and written and has the power to build its context because the system has been developed in this way for making meaning out of context as it was given (Halliday and Matthiessen, 2013) Systemic Functional Linguistics is one the approach that studies the use and its functions of language in context. Michael Halliday is a pioneer of this model of grammar description in which the social semiotic approach is also considered. SFL considered the language as an interactive mode that can be realized by various structures and semantics is one of the key units of it. Language has three meta-functions: ideational (transitivity), interpersonal (mood) and textual(theme-rheme).

Textual meaning covers theme-rheme structure that is realized through lexico-grammatical resources. However, there is also another approach to studying these meta-function clauses relations. It finds out logical components in clauses to build semantic relations. Although clause complex is categorized as a structural entity and also sketches out the functional organisation of a sentence. In simple words, it describes how the various and number of clauses of a sentence are connected logically and semantically. Halliday (1994) declared it as "the functional semantic relations that make up the logic of natural language" (p. 216). These logics are directly pursuant to the propositions, their all components and constituents and relations (Ellis 1987, p. 108). A text can be coherently composed when all these aspects of propositions and content are semantically connected and related. This kind of relationship is inherent in the structure of clause complex and identified in the interdependent clauses. Ellis narrated it as "logical linguistic structure... relations between propositions represented by clauses and sentences in parataxis and hypotaxis, with their conjunction and relevant adjuncts" (Ellis, 1987, p. 124).

Clause complexes build the interdependent system that consists of two systems: "taxis" and "logico-semantic relations". Both systems work together simultaneously to move the discourse forward which provides the "functional framework for describing the clause complex" (Halliday & Matthiessen, 2014). This interdependency network has been shown in Figure.

Figure 1. System of Clause Complexes (Halliday & Matthiessen, 2014)



Source: The Author

1.4 Previous Studies

Undoubtedly, research and literature are scarce, particularly in this domain in which AI-generated text and its lexico-grammatical features individually or in comparison to humanly produced text have been studied. However, few researchers tried to explore this landscape such as Li et al (2019 cited in Markowitz1, 2023) affirmed that AI-generated texts are a close resemblance to human-written text by evaluating the news articles. The finding of this research holds the premise for the application of AI in various applications like journalism and content creation. Still, it is ambiguous to define; how both kinds of texts are different from each other. Similarly, Hohenstein and Jung (2020) also claim that AI-generated messages are less wordy and less analytical, conversational and rich with affective content. However, it was difficult to mark the difference between AI-generated messages (Google Allo) and standardised messages of human beings on WhatsApp with great accuracy (Mieczkowski et al., 2021; E. Clark et al., 2021; Köbis & Mossink, 2021; Kreps et al., 2022). It has been concluded that AI-generated text follows the constructed of efficacy and positivity biased and is observed as more emotionally opposite to human text.

Markowitz et.al. (2023) also did research to find out the differences, based on analytical writing, descriptiveness and readability in which the study of function words, and structural complexity were conducted. The study of hotel reviews and news headlines (randomly selected humanly and AI-generated data) reached these claims that AI-generated text is more effective, less readable, and more descriptive. Secondly, humanly written text is intentionally deceptive while inherently deceptive is the feature of AI-generated text.

Upon reviewing the existing literature, it becomes apparent that there is a dearth of studies specifically examining clause structure in AI-generated argumentative essays as well as in comparison to Human-written argumentative essays

1.5 Research Questions

The current research tried to uncover the facts about AI-generated argumentative text regarding the system of clauses complexes by providing the answers to the following research questions.

- What kinds of taxis and logico-semantics relations are identified in ChatGPT-generated argumentative essays?
- How do AI-generated argumentative essays vary from human-written argumentative essays regarding taxis and logico-semantic relations?

2. Research Methodology

2.1 Types of Study

This study used the SFL theoretical framework by employing the system of clauses complexes (Halliday & Matthiessen, 2014) to study logical meta-functions in AI-generated and Human-written argumentative essays.

2.2 Data Collection

Current research collectively studied the 30 argumentative essays that consisted of three datasets; 10 -AI-generated essays from ChatGPT, 10 EN human-written essays from LOCNESS and 10 ESL human-written essays from ICLE.

2.3 Tool for the Study

Two tools were used during this research: ChatGPT and UAM tool.

- 1) ChatGPT AI chatbot was deployed for generating the argumentative essays.
- 2) All thirty essays were annotated manually by using the UAM tool.

2.4 Research Procedure

To conduct the comparative study of AI-generated argumentative and Human-written argumentative essays regarding taxis and logico-semantic relations, the following steps were systematically utilized;

1. Corpus was collected and generated from three different sources ChatGPT, LOCNESS and ICLE.
2. Classified the corpus into two major datasets: human-written essays and ChatGPT-generated essays.
3. Human-written essays were further categorized into native and non-native essays
4. Corpus was annotated manually by utilizing the UAM tool and by approaching theoretical framework of the system of clauses complexes.
5. Quantitative analysis of understudied taxis and logico-semantic relations was conducted in each dataset.
6. Comparative analysis of these features was directed among all three datasets.

3. Finding and Discussion

3.1 Finding and Analysis of Clauses

The findings which are based on percentages, reveal that Pakistani writers use both clause simplexes and clauses complexes but the percentage of clause simplexes is comparatively high as shown in the following table 3.1.

Table 3.1 Type of Clauses Boundaries and their Percentages

Type of Clauses	AI-Generated AEs	Human-Written AEs (native + non-native)	Native	Non-native
Clause Simplexes	30	37	36	39
Clause Complexes	56.8	45.5	46	45
Clause Embedded	13.1	14.5	17	12

As previous studies reveal that written discourses have more complex, integrated and detached and explicit features (Chafe, 1981, Hildyard & Olson, 1978). Current research starts with the study of kind of clause: clause complexes, clause simplexes and clause embedded and data shows that AI-generated AEs carry a high proportion of clause complexes (56.8 %) in comparison to humanly written argumentative text (30 %).

However, the appearance of clause simplexes is lower in both understudied datasets. The percentage of clause simplexes is higher in humanly written text opposite to the AI-generated texts as shown in table 3.2.

Table 3.2 Examples of Clause Complexes and Clause Simplexes

AI-Generated Clause Simplexes	Human-Written Clause Simplexes
Transportation is an integral part of our daily lives, shaping our experiences and interactions	This will boost the industrial sector and will create more opportunities for young technical people
By prioritizing sustainable transportation solutions, we can create healthier and more livable communities while reducing our carbon footprint.	We should overcome these causes if we want to stop the evil product manufactured due to these raw materials.

3.2 Finding and Analysis of Taxis

These findings uncover the huge differences between AI-AEs and HW-AEs regarding the appearance of parataxis and hypotaxis. Below table 3.3 provides the percentage of parataxis and hypotaxis. Both datasets mostly construct the clause complexes by building the combination of two equal clauses. However, AI texts have higher percentage (67%) as compared to Human-written texts 40%. On the other hand, hypotactic relations appear at 32.8% and 35% respectively as represented in table 3.3.

Table 3.3 Percentage of Taxis

Type of Clauses	AI-Generated AEs	Human-Written AEs	Native	Non native
Paratactic	67.1	39.5	46	33
Hypotactic	32.8	35	24	46

The aforementioned findings highlight that Pakistani writers construct a combination of equal-ranked clauses and unequal-ranked clauses with almost same percentage for the building the proposition for the argumentation. Paratactic constructions are 50.1% while hypotactic are 49.8%. There is only a 0.3% difference between the two these taxis. The examples of following taxis have been noted in table 3.4.

Table 3.4 Examples of Paratactic and Hypotactic

AI-Generated Paratactic and Hypotactic	Human-Written Paratactic and Hypotactic
We can drive positive change, protect the environment and enhance the well-being of future generation	What is wrong, and what can we do about it?
While money can influence behaviours, individuals bear personal responsibility for their actions	Poor people beg for money so, money is also the cause of begging.
We can strive for a world where money catalyzes positive change rather than a source of Moral Compromises	As more and more people use cars, traffic in city centres during rush hour comes to a near standstill.

3.3 Findings and Discussion on Projection Relations

Projection relations are identified as markers of maturity through which writers incorporate the mental process, references, sayings and quotations in the writings. AI generates these relations almost with same equation likely to humans as highlighted in table 3.5.

Table 3.5 Percentage of Projection Relations

Projection Relations	AI-Generated AEs	Human-Written AEs	Native	Non-native
Paratactic	0.3	0.5	0.62	0.38
Hypotactic	2.2	1.94	0.42	3.46

Both datasets construct projection relations relatively high with hypotactic construction, opposite to paratactic.

3.4 Paratactic Projection Relations

The logico-semantic relations of projections in AI texts do not show a preference for constructing ideas and locutions in combination with equally ranked classes. The available data does not indicate any related constructs in this regard. There is only one instance of an idea-based relation, has been found in the entire corpus. However, humans construct locution relations with paratactic structures in various ways, as shown in the table 3.6.

Table 3.6 Percentage of Paratactic Projection Relations

Paratactic-Projection Relations	AI-Generated AEs	Human-Written AEs	Native	Non-native
Idea	0.3	0	0	0
Locution	0	0.5	0.62	0.38
Verb says	0	0.1	0.21	0
Question	0	0	0	0
Offer and command	0	0.09	0	0.19
Verb says with circumstance	0	0.1	0.21	0
Verb associate with speech connotation	0	0	0	0
Verbal processing use of writing verb	0	0	0	0
Verb embodied with circumstances or semantic features	0	0.1	0.21	0
Statement	0	0.09	0	0.19

Moreover, humans utilize the relations of the verb say, offer and command, and the verb say with circumstance and statements in their writings while AI shows the lack of proficiency regarding these sub-categories.

3.5 Hypotactic Projection Relations

AI-generated texts carry less projection relations in their writings as compared to human written text. It doesn't build mental process relations with hypotactic constructions such as, I think. However, locution cases have been found in the AI-generated texts in which questions and circumstance-based sayings are included.

In comparison to human-written AEs, humans produce both kinds of relations in their writings collectively; mental and verbal as displayed in the table 3.7. Moreover, it has been found that non-native writers use highly mental process constructions while native corpus has no constructions regarding it like AI-texts. Notably, AI-generated AEs utilize more relations of locution in their content as compared to humanly cases.

Table 3.7 Percentage of Hypotactic Projection Relations

Hypotactic-Projection Relations	AI-Generated AEs	Human-Written AEs	Native	Non-native
Idea	0	2.02	0	4.04
Locution	2.2	1.94	0.42	3.46
Verb says	0	1.3	0.21	2.5
Question	0.32	0	0	0
Offer and command	0	0	0	0
Verb says with circumstance	0.32	0.095	0	0.19
Verb associate with speech connotation	0.63	0	0	0
Verbal processing use of writing verb	0	0	0	0
Verb embodied with circumstance or	0.95	0	0	0

	semantic features				
	Statement	0	0.39	0.21	0.58

Table 3.8 Examples of Paratactic Projection and Hypotactic Projection

AI-Generated	Human-Written
Paratactic Projection	Paratactic Projection
.... others believe it is simply a tool with no inherent moral value.	Some say increasing prices om petrol and taxing of the use of roads will help.
AI-Generated	Human-Written
Hypotactic Projection	Hypotactic Projection
Some argue that money is essential for progress and development	Some say increasing prices on petrol and taxing the use of roads will help

3.6 Finding and Discussion on Expansion Relations

The study shows that expansion relations appear highly in both AI-generated text and human-written text collectively. The percentage of paratactic constructs in this regard is notably higher as compared to hypotactic construction. Moreover, AI-generated AEs carry 8% higher paratactic-expansion cases opposite to humans while the relations of hypotactic-extension are 3% higher in human text as highlighted in table 3.9. In three further categories of expansions. The extension relations are constructed noticeably as compared to elaboration and enhancement. These findings suggest that AI is designed to frequently produce extension relations that even exceed humanly constructions. There is a similar trend has been found in the cases of paratactic extensions. These relations help to provide additional details, elaborate on ideas, and enhance the overall content of their writings. AI is designed for this approach that often leaves humans behind. It can be inferred that humans considered the concept of context in their discourse and sometime they know about the intellectual level and background of the participant to whom they are discussing and engaging.

Similarly, hypotactic extensions are generated 3.4% higher than human-written text. Conversely, hypotactic enhancement constructions appear less frequently in AI-generated text as compared to human-written text. The nature of the genre seems to contribute to the unfavourable occurrence of elaborations by both AI and humans' discourses.

Table 3.9 Percentage of Expansion Relations

Expansion Relations		AI-Generated AEs	Human-Written AEs	Native	Non-native
Paratactic		30.4	22.2	25.9	18.65
	Extension	26.6	19.7	22.8	16.73
	Elaboration	1.59	1.67	1.8	1.54
	Enhancement	2.2	0.8	1.25	0.38
Hypotactic		13.3	16.3	14.1	18.65
	Extension	3.4	0.78	0	1.35
	Elaboration	0.32	0.2	0.21	0.19
	Enhancement	9.5	15.4	13.7	17.1

3.7 Paratactic Extension Relations

The logico-semantic relations of extensions: Addition, variation and alternation have also been studied. It is found that AI generates only positive addition (21%) and adversative addition (5%) during argumentation while negative addition, variation, alternation does not occur in AI-text. However, humans construct all sub-types of logico-semantic relations in their writings during argumentation. It can be confirmed that AI might not design with the full range of variations and stylistic choices; made by humans or the training data of AI is biased in some domains. So, AI-generated text shows its limitation in this domain as highlighted in table 3.10

Table 3.10 Percentage of Paratactic Extension Relations

Extension Relations		AI-Generated AEs	Human-Written AEs	Native	Non-native
Addition		26.6	18.4	21.41	15.5
	Positive additive	21.5	14.6	16.8	12.5
	Adversative additive	5.08	3.78	4.5	3.08
	Negative addition	0	0	0	0
Variation		0	0.69	0.62	0.77
	Replacive	0	0.5	0.42	0.58
	Subtractive	0	0.2	0.21	0.19
Alteration		0	0.6	0.83	0.38

3.8 Hypotactic Extension Relations

As mentioned previously hypo-extension relations are constructed frequently less as compared to para-extension. This study reports only 3.4% of hypotactic extension relations in AI-generated texts while humanly texts carry 0.58%. It is higher than human-written text. It is noticed that AI-generated text shows a similar trend for logico-semantic relations to natives. There is no occurrence regarding adversative relations, variations, alternations in both native and AI-generated text as represented in the table 3.11

Table 3.11 Percentage of Hypotactic Extension Relations

Hypotactic Extension Relations		AI-Generated AEs	Human-Written AEs	Native	Non-native
Addition		3.49	0.58	0	0.96
	Addition	1.27	0.39	0	0.58
	Adversative addition	2.2	0.19	0	0.38
Variation		0	0.09	0	0.19
	Replacive	0	0.09	0	0.19
	Subtractive	0	0	0	0
Alterations		0	0.09	0	0.19

Table 3.12 Examples of Paratactic Extension and Hypotactic Extension

AI-Generated Paratactic Extension	Human-written Paratactic Extension
Additionally, expanding and enhancing public transportation systems can alleviate congestion, improve urban mobility, and enhance the quality of life.	They take bribes, and start corruption.
Police favoring the rich and powerful are often prioritized, while the needs of marginalized are neglected, perpetuating a cycle of systemic injustice.	This may deter people from using their cars or it may just push them onto country roads increasing rural traffic.
AI-Generated Hypotactic Extension	Human-written Hypotactic Extension
The relentless pursuit of financial gain, without considering the consequences, creates a fertile ground for immoral behaviour. money obtained from wrong means cannot give peace.

3.9 Paratactic Elaboration Relations

The finding regarding these relations points out writers try to strength their arguments by explaining in the form of examples and clarification in some extent as compared to AI as represented in table 3.13. It can be inferred that AI doesn't explicitly use the feature of descriptive reports in the argumentative genre, due to the nature of this academic genre.

Table 3.13 Percentage of Paratactic Elaboration Relations

Paratactic Elaboration Relations	AI-Generated AEs	Human-Written AEs	Native	Non-native
Clarification	0.95	1.01	1.25	0.77
Exposition	0.32	0.1	0.21	0
Exemplification	0.32	0.56	0.42	0.77

3.10 Hypotactic Elaboration Relations

These logico-semantic relationships are not highly appeared in both AI and human texts as mentioned in table 3.14. There are few occurrences; that have been found in the understudied datasets of the corpus as represented in table 3.15.

Table 3.14 Percentage of Hypotactic Elaboration Relations

Hypotactic Elaboration Relations	AI-Generated AEs	Human-Written AEs	Native	Non-native
Clarification	0.3	0.29	0	0.58
Description	0	0.29	0.21	0.38

Indeed, this genre could be a plausible explanation for the absence of description. It may be suitable in other genres such as descriptive reports etc. (Srinivas, 2004; Brisk & Rosa, 2014). Few examples, represented in following table 3.15, are extracted from the understudied datasets.

Table 3.15 Examples of Paratactic Elaboration and Hypotactic Elaboration

AI-Generated Paratactic Elaboration	Human-Written Paratactic Elaboration
Transportation has played a pivotal role in shaping societies and economies, revolutionizing the way we live and interact.	The problem is obvious-there are too many cars on Britain's roads.
AI-Generated Hypotactic Elaboration	Human-Written Hypotactic Elaboration
Transitioning to sustainable transportation is not without challenges, including high initial costs and the need for infrastructure developments.	The people became very greedy that they don't know.

3.11 Paratactic Enhancement Relations

Enhancement relations with paratactic constructs show that primary clauses enhance or qualify another clause by providing the additional or required information related to time, place, manner, cause and condition. In simple words, one clause qualifies the other clause to give the proper and comprehensive proposition. However, the findings in the following table 3.16 display that AI does not show any inclination to construct these logical relations by using equal-ranked clauses.

Table 3.16 Percentage of Paratactic Enhancement Relations

Paratactic Enhancement Relations		AI-Generated AEs	Human-Written AEs	Native	Non-native
Temporal		0	0.21	0.42	0
	Same time	0	0.21	0.42	0
	Later time	0	0	0	0
Spatial		0	0	0	0
Manner		0	0	0	0
	Means	0	0	0	0
	Comparison	0	0	0	0
Conditional		0	0.2	0.21	0.19
	Positive	0	0.2	0.21	0.19
	Negative	0	0	0	0
	Concession	0	0	0	0
Causal		2.22	0.40	0.62	0.19
	Cause	0	0.10	0.21	0
	Effect	2.22	0.3	0.42	0.19

Noticeably, the only causal relations have been found in AI texts in which proposition discusses the effects relations as represented in the table 6.14 while humans utilize the various relations for these constructions.

3.12 Hypotactic Enhancement Relations

The enhancement relations in the case of hypotactic expansion clause constructions occur exclusively in AI-generated essays. It covers temporal, spatial, manner and causal conditions relations in their text with the combination of unequal clauses like a human, although their percentages are less than human text. It is noticeable that AI does not generate any conditional relations in its texts with the lexico-grammatical resource such as *if*. On the other hand, humans highly construct the positive conditional hypotactic clause complexes as highlighted in Table 3.18. It can be inferred from this difference that humans have the intellectual capacity to create hypothetical senior and logical dependencies to justify the claims and proposition according to the context of the discourse while AI doesn't train in this approach as shown in 3.17.

Table 3.17 Percentage of Hypotactic Enhancement Relations

Hypotactic Enhancement Relations		AI-Generated AEs	Human-Written AEs	Native	Non-native
Temporal		1.59	3.85	3.3	4.4
Spatial		0.32	0.21	0.42	0
Manner		2.22	2.1	2.08	2.31
	Means	2.22	1.7	1.87	1.54
	Comparison	0	0.29	0.21	0.38
	Quality	0	0.19	0	0.38
Conditional		0	2.68	2.91	3.08
	Positive	0	1.79	2.29	2.5
	Negative	0	0.2	0.21	0.19
	Concessive	0	0.61	0.42	0.38
Cause		5.4	6.1	4.99	7.3
	Result	0.32	1.3	1.2	1.54
	Purpose	1.9	0.9	1.04	0.77
	Reason	3.17	3.85	2.7	5

Table 3.18 Examples of Paratactic Enhancement and Hypotactic Enhancement Relations

AI-Generated Paratactic Enhancement	Human Written Hypotactic Enhancement
Greed, materialism, and the lust for power often accompany the accumulation of money, resulting in unethical behaviour such as exploitation, fraud and dishonesty.	If public transport is improved, more might use it, and ease the strain on roads.
AI-generated Hypotactic Enhancement	Human-written Hypotactic Enhancement
By recognizing and nurturing the non-materialistic aspects of our lives, we can cultivate a more fulfilling and balanced existence.	Money makes blind them so they do not think in the right way.

4. Conclusion

This minor study marked the differences and similarities between AI-generated AEs by ChatGPT and human-written AEs regarding the system of clauses complexes (Halliday & Matthiessen, 2014). The corpus that consisted of a total of thirty essays has been collected from three different resources: ChatGPT, LOCNESS and ICLE. Findings show that although the ChatGPT chatbot was designed and atomized by using the corpus of human language but it still highlights variations during the constructions of logico-semantic relations. AI generates more complex sentences than humans. Secondly, in the case of taxis, the percentage of paratactic is comparatively higher in AI however, hypotactic construction is also generated but less in numbers. On the other hand, in human texts, native writers also notably construct clause complexes with the combination of equal clauses as compared to unequal clauses while non-native writers used more hypotactic clauses. It can be inferred that AI is near to human text in this context but with a native community. Thirdly, in hypotactic relations, AI did not favourably generate the mental relations in the clause as compared to humans' discourse. They use it to show their own stance and idea to build the claim. Fourthly, extension relations with paratactic construction showed their exclusive occurrences in AI-generated writings while hypotactic enhancement appeared highly in human texts. Moreover, in extension cases, AI showed its inclination only towards the addition and neglected the constructions of variation and alternation during the claim's constructions and argumentation. AI seems less proficient to compose the text by utilising, temporal, spatial and conditional-causal relations for argumentations and to solidify their claims. It was noticed that AI did not generate any clause/ proposition by utilizing the conditional clauses: positive, negative and concessions etc. It was also observed that elaboration relations appeared less in both AI and human texts with almost the same ratio.

All these observed differences mark the major difference between AI and humanly written discourse regarding the system of clause complexes. With the reference of this study, AI creators and developers can get insight and also do actions to reduce the differences and to reach near to human discourse. Moreover, these findings also help English language teachers and learners to understand the worth and limitations of AI who try to use AI-text as learning and teaching material.

Although findings regarding taxis and logico-semantic relations in both human and AI-generated texts provide insight to both AI-developer, Linguist, ESP learners and teachers these are following limitations:

- Data is limited, the researchers utilize only 30 essays. It can be increased to build strong claims.
- The dataset of non-native AEs contained the essays of ESL learners. EFL can be included to do a comparative study
- SFL provides three types of meanings: ideational, textual and interpersonal. Current research only explored logical functions.

Funding: This study was not funded in any shape or form by any party.

Conflict of Interest: The authors declare that they have no conflict of interest.

Bio-note:

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