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Evaluating the Role of Artificial Intelligence in Supporting Usage - Based Approaches to Grammar

A B S T R A C T

This study investigates grammatical trends in texts generated by artificial intelligence and human learners. The study puts to the test a fundamental principle of usage-based grammar: language is learned through repeated exposure to patterns. A direct comparison is conducted between AI-generated writings and language learners' essays. Quantitative approaches count words, sentences, and grammatical errors. Qualitative analysis detects trends in sentence structure and specific qualities such as, the use of past tense. Finding out if AI models adhere to usage-based grammar rules is the aim. Comparing the two groups' mistake types is another objective. The results show that whereas human writing varies, AI output is very constant. Almost no grammatical errors were found in AI articles, according to the study. Expected errors in human texts include omissions and overgeneralizations. The findings also demonstrate that AI makes greater use of components like the past tense and plurals. This study demonstrate that the outcomes of usage-based learning are operationally replicated by AI. Training on massive datasets results in highly consistent output. The ongoing process of language acquisition is reflected in human output. The study comes to the conclusion that AI is a powerful instrument for confirming frequency-based linguistic theory, but it does not model the human cognitive journey. Future research should investigate different AI models and learner proficiency levels.

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تقييم دور الذكاء الاصطناعي في دعم المناهج القائمة على الاستخدام في دراسة النحو

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الملخص

تستقصي هذه الدراسة الاتجاهات النحوية في النصوص التي تُنتجها تطبيقات الذكاء الاصطناعي مقارنة بتلك التي يكتبها المتعلمون من البشر. تختبر الدراسة مبدأً أساسياً من مبادئ النحو القائم على الاستخدام (usage-based grammar)، والذي يفترض أن اللغة تُكتسب من خلال التعرض المتكرر للأنماط اللغوية. ولتحقيق ذلك، تم إجراء مقارنة مباشرة بين نصوص الذكاء الاصطناعي ومقالات متعلمي اللغة. تعتمد الدراسة على منهجيات كمّية (quantitative approaches)لعدّ الكلمات والجمل، ورصد الأخطاء النحوية. كما تستخدم مناهج نوعية (qualitative analysis) للكشف عن الاتجاهات العامة في بناء الجملة، وخصائص محددة مثل استخدام صيغة الماضي .(past tense) الهدف الأساسي هو معرفة ما إذا كانت نماذج الذكاء الاصطناعي تلتزم بقواعد النحو القائم على الاستخدام، إضافة إلى مقارنة أنماط الأخطاء (mistake types) بين المجموعتين .تُظهر النتائج تبايناً واضحاً؛ فبينما يتسم إنتاج الذكاء الاصطناعي بثبات كبير، تميل النصوص البشرية إلى التنوع والتفاوت. وقد كشفت الدراسة عن خلُوّ نصوص الذكاء الاصطناعي تقريباً من الأخطاء النحوية، في المقابل، احتوت النصوص البشرية على أخطاء متوقعة مثل الحذف (omissions) والتعميم المفرط .(overgeneralizations) كما تشير النتائج إلى أن الذكاء الاصطناعي يوظف بعض العناصر اللغوية، كصيغة الماضي وصيغ الجمع(plurals) ، بشكل أكثر كثافة .تخلص هذه التحليلات إلى أن أداء الذكاء الاصطناعي يحاكي عملياً نتائج التعلّم القائم على الاستخدام. فنتائج تدريب هذه النماذج على كميات هائلة من البيانات تتسم بالاتساق والدقة. في المقابل، يعكس الإنتاج البشري الطبيعة المستمرة والمتطورة لعملية اكتساب اللغة. تستنتج الدراسة أن الذكاء الاصطناعي يمثل أداة قوية للتحقق من النظريات اللغوية القائمة على التكرار (frequency-based linguistic theory)، إلا أنه لا يمثل نموذجاً محاكياً للرحلة المعرفية البشرية. توصي الدراسة بإجراء أبحاث مستقبلية تتناول نماذج مختلفة من الذكاء الاصطناعي ومستويات متنوعة من كفاءة المتعلمين.

الكلمات المفتاحية: متعلمو اللغة الإنجليزية كلغة أجنبية ، تأثيرات التكرار، القياس، تحليل الأخطاء، التعلم البنائي، اللغة الوسيطة.

Introduction

Usage-based grammar is a key concept in language learning. According to this hypothesis, language is learned by repeated exposure to patterns. By repeating words and sentences, our brains can learn the rules in this particular area. This technique is necessary for learning grammar (Ellis, 2002). Artificial intelligence is revolutionizing several areas. Modern language models such as ChatGPT may now generate writing that is fluid. These models are trained by predicting words from massive volumes of language data (Chen et al., 2024; Du et al., 2023; Goncharenko & Krasniuk, 2024; Li & Xing, 2021). This training involves a great deal of repetition. It resembles a fundamental step in the usage-based grammar concept.

Nonetheless, there is a noticeable void in the existing research. Few studies directly evaluate whether AI-generated text complies with usage-based grammar rules, despite the fact that AI learns from frequency. Additionally, there are no direct parallels between the grammatical errors made by AI and those made by human language learners. Therefore, it is uncertain if this language theory can be consistently assessed using artificial intelligence. The goal of this study is to bridge that gap. Its objective is to apply a usage-based lens to the analysis of grammatical patterns in AI-generated text. The frequency and kinds of errors in AI with human writing are specifically examined. The study examines how concepts such as analogy and frequency show up in both results.

While AI accurately depicts the results of frequency-driven learning, it does not accurately replicate the human acquisition process, according to the main argument of this paper. Human language will display the unpredictability and errors associated with dynamic learning, according to the thesis, but AI grammar will be extremely consistent and error-free. First, usage-based grammar theory is reviewed. After that, the comparison of AI and human literature is covered. Following that, the analysis provides both qualitative and quantitative results. The discussion demonstrates the relevance of these results to linguistics and language instruction. Lastly, the conclusion highlights the key discoveries and calls for more study.

Usage-based grammar

Usage-based grammar is a reaction to the generative doctrine that language rules are pre-wired (Chomsky, 1965; Pine &Tomasello, 2005). Instead, it treats language as a system of patterns. Learners acquire a language by hearing it around them. They start to develop grammatical rules through interaction and exposure. The more learners encounter a linguistic construction, the stronger the mental representation it becomes (Diessel, 2017). Upon hearing a construction, learners detect patterns in a language. For example, you hear “how are you?” many times. Your brain will deal with it as a construction. There will be no need to analyze the position of the words “how” or “you”. Language, thus, is built by practice and frequency. Your mind works as a statistical device. It counts the number of times a construction occurs (Behrens, 2009).

Those constructions are bottom-up. We use the language first. Through frequent speech, our minds infer the pattern. Later, we will call it a rule (Diessel, Dabrowska, & Divjak, 2019; Langacker, 2011; Bybee, 2008). In language, you hear people say, "I'm hungry," "I'm tired," "I'm going." Your mind notices that "I" is always followed by an adjective or present tense verb. This "path" that forms in your mind is what we later call a rule. The bottom is raw data, simple "everyday speech" such as street talk, stories, songs, or shouts. The top is mental abstraction, the "general law" or "rule." The journey begins with real-life speech and ascends until you reach a law in your mind. In colloquial speech, we don't study grammar rules, yet we never make errors. You say, "I have a car," "I have a job," "I have an idea." It's impossible to say, "I have someone going" or "I have someone who." How do you know? Not because a book told you, but because you heard the [I have + name] pattern millions of times until it formed a "corridor" in your mind. You built the rule from the bottom up (hearing) to the top (inference).

The constructions are not merely a syntactic structure. Instead, imagine language as ready-made "building blocks" called constructions (Goldberg, & Suttle, 2010, Diessel, 2017). In school, we were taught that a sentence is just a "structure": (verb + subject + object). In this theory, they say: No! A sentence isn't an empty structure that we fill with words; it's a living template. Constructions are pairs of meaning and form. They range from simple words to more complex sentences. The idea is that any "construction" in your language is a "two-sided coin". For example, the "Him be a doctor?" Construction. Imagine a very dishonest person telling you they've become a doctor, and you reply in English: "Him, a doctor?!" The structure consists of Object pronoun (Him) + noun (doctor). However, the meaning is either Ridicule or utter disbelief. Why is it a "template"? If we apply traditional (school) grammar rules, this sentence is "incorrect" because there's no verb (is). But in the mind of an English speaker, this is a ready-made template used only for sarcasm. You don't construct it; you recall it from memory as a single unit.

A related example is the "One More X" Construction For example: "One more word, and you're grounded!" The form consists of:

[One more + noun] + [and + result].

At the semantic level, it is an explicit threat. Why is it a "construct"? Because you don't mean "one more word" as a number, but rather "If you open your mouth, I'll punish you." This pair (form + threatening meaning) is what learners memorize through frequent use. This "pair" (form + specific meaning) is stored in your mind as a single unit that the theory calls Construction. It progresses from "simple words" to "complex sentences" (Langacker, 2011).

Analogy and Overgeneralization

These constructions are activated through the process of analogy. Simply put, analogy is using the stored patterns in the mind to produce new forms (Behrens, 2017). It involves the comparison of one linguistic form to another. Learners apply what they already know to new situations. The phrase “drive someone banana” is an analogy to “drive someone crazy”. The learners compare the two forms. These comparisons expand their repertoire of possible constructions (Fischer, (2018).

However, the analogy may result in a negative effect on learners (Rescorla, 1980). They may expand specific rule to broader patterns, i.e. -ed rule “goed instead of went”. This overgeneralization of rules lead to errors in learning. It usually occurs of high-frequency words or constructions (Ambridge, Pine, Rowland, Chang, & Bidgood, 2013; Cordes, 2017). It happened at the phonological, syntactic, and sematic level. Learners read, listen, and interact with the target language in various contexts (Wei, Yang, & Xiang, 2025). Over time, this exposure shapes their ability to recognize, retrieve, and combine constructions. It then manifested in the way they speak, and write. Learners start by imitating sentences and gradually extend these patterns to novel contexts (Zyzik, 2009).

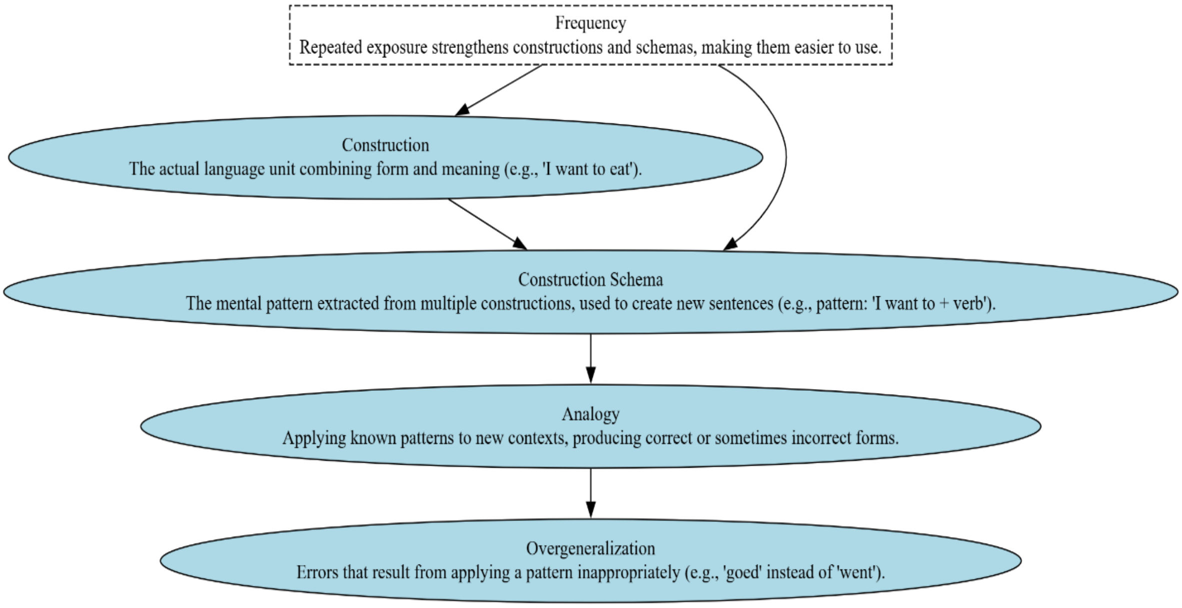

Figure 1: Relationships Between Constructions, Schemas, Analogy, and Frequency

Language learning in Artificial Intelligence

Language usage by ChatGPT and other AI models is similar to that of learning a second language. These methods don't begin with specific grammatical rules or formal instructions. Instead, they manage enormous amounts of content from websites, books, journals, and digital communications. This input repeatedly exposes words and phrases that occur in different contexts. As a result of this exposure, the models begin to recognize patterns in the word sequence. Certain combinations turn into constructs when they appear frequently in multiple cases.

In this sense, constructions develop through repeated exposure to linguistic material. Step by step, this exposure strengthens associations between words and structures (Brown et al., 2020, Choshen et al., 2021, p. 3).

These parallels lead to an analogy. ChatGPT generates new sentences based on patterns in existing sentences rather than explicit rules. For example, it creates problems by stressing auxiliary (Dunn, 2022, p. 8). Humans have comparable learning styles. Mirchandani et al. (2023) claim that they combine well-known statements like "I like apples" to produce new ones like "I like oranges" (p. 5). Both methods generate new sentences by utilizing well-known patterns.

Errors reflect the process that drives this learning. Learners sometimes use forms like "comed" or "runned," and ChatGPT occasionally misapplies irregular verbs (Eskildsen, 2012; Zou, Huang, & Xie, 2023, p. 3). These errors are not random. They reflect attempts to generalize rules. In addition, they identify which patterns are being internalized (Mohammed & Aljanabi, 2024). Early structures are simple, i.e. fixed phrases like “My name is”. Gradually, they expand into longer sentences as exposure increases (Choshen et al., 2021). At every stage, analogy plays a great role in the extension of existing patterns to new contexts (Dunn, 2022, p. 12).

Adaptation arises through repeated input. ChatGPT can change style between casual and formal text. It learns constructions linked to each style. Learners adapt language for classrooms, work, or informal conversation (Wang et al., 2023, p. 4). Exposure to specific contexts encourages learners to use appropriate constructions. Adaptation is a sign that frequency and analogy influence flexible use of language.

Grammar acquisition via usage and repetition has been the subject of several research (Aslin & Newport, 2012; Behrens, 2009; Brown, 1998; Bybee, 2006, 2008; Diessel et al., 2019; Gries, 2008; Lieven, 2010; Romberg & Saffran, 2010; Tan & Shojamanesh, 2019). Other research has examined how AI generates language (Dong et al., 2022; Goldberg, 2017; Hu et al., 2023; Kovács et al., 2023; Liang et al., 2024; Paris et al., 2013; Wang et al., 2023; Zarrieß et al., 2021; Zhang et al., 2023; Hasan. 2025; Al-Kareem, 2025).

Few research, nonetheless, have made a direct comparison between AI models' grammar learning and human usage-based grammar. Because of this mismatch, it's uncertain if AI can support usage-based strategies.

Research Aims

The study aims at:

1. Examining how usage-based grammar relates to language learning in AI systems.
2. Comparing AI-generated texts with texts written by EFL learners
3. Investigating frequency effects and recurring error patterns in AI-generated texts.
4. Assessing AI models as tools for studying human language acquisition.
5. Connecting human and artificial learning systems.

Research Questions

1. To what extent do AI language models follow usage-based grammar?
2. How do the grammatical errors in AI-generated texts compare with those of EFL learners in terms of type, frequency, and distribution?
3. To what degree do frequency and analogy shape the grammar of AI models when compared to human learners?
4. Can AI models be considered reliable instruments for exploring and testing usage-based theories of grammar?

Research Design

This study used a mixed-method research design to address the research problems. Both quantitative and qualitative data were collected. Statistical data was used to determine the frequency of grammatical constructions. Qualitative data was used to identify error types and analogy trends. The study also looked at frequency effects, analogies, and error patterns. The focus of this study on the application and generalization of patterns, as opposed to research that just looks at grammatical accuracy.

Participants and Data Collection

The human participants were 50 third-year morning-study students. They were enrolled in the English program at the University of Basrah, College of Education-Qurna, Iraq. According to the CEFR scale, their level of English proficiency was higher intermediate (B2). The study was carried out in the academic year 2024–2025. One of four essay topics—education, social media, technology and learning, or hobbies—was chosen by each student. "Write an essay about [topic]" was the prompt for each topic. Share your thoughts and provide examples. Students were required to write a minimum of 250 words. Each final essay had a word count of 250–300. Essays with fewer than 250 words were not accepted. Fifty student texts—one for each student—were generated by this procedure. There were about 13,000 words in the entire student corpus.

Chat GPT (GPT 4, May 2025 version) was used to produce the AI data. Repeated prompts were used to generate the AI texts. To create a diverse sample, these questions addressed both common and rare grammatical rules. One example question for standard rules was "Write a 500-word text using the present perfect tense five times." "Use the subjunctive mood (e.g., 'I suggest that he go')" is an example prompt for unusual rules. Fifty AI texts in all were produced. There were around 1,000 words in each AI text. There are about 50,000 words in the total AI corpus. For both quantitative and qualitative analysis, this size was suitable.

Procedures

All procedures were performed in the same way for both human and AI data to ensure reliability. The investigation was enhanced by the use of triangulation. The texts were evaluated separately by two certified linguists. The error lists were then compared. On 95% of the errors, an agreement was reached. Until an agreement was achieved, the remaining 5% were discussed. Linguists addressed any misunderstandings and approved any errors. They also investigated if usage-based learning was the cause of the errors. This expert assessment improved accuracy and reduced bias.

For statistical analysis, SPSS version 26 was used. Excel was used to create simple charts. For corpus analysis, AntConc software was used to count words and grammar patterns. All student essays were typed into Word files without editing the errors. Each file was named “Student_01.txt” to “Student_50.txt.” All AI outputs were saved as “AI_01.txt” to “AI_50.txt.” No editing was performed on the AI texts. All student files were placed in one folder, and all AI files in another folder.

Analysis and Results

Research Question 1: To what extent do AI language models follow usage-based grammar?

To determine if AI follows usage-based grammar, we must first examine the descriptive patterns of language output in both human and AI writing. The usage-based grammar theory states that linguistic structure develops from recurrent patterns of real language use. Table 1 compiles descriptive information for numerous significant indicators.

Table 1. Descriptive Statistics of AI and Human

Statistics	Word Count (Human)	Word Count (AI)	Sentence Count (Human)	Sentence Count (AI)	Overgeneralization (Human)	Overgeneralization (AI)	Omission (Human)	Omission (AI)	Misformation (Human)	Misformation (AI)	Frequency Past Tense (Human)	Frequency Past Tense (AI)	Frequency Plural (Human)	Frequency Plural (AI)	Frequency Articles (Human)	Frequency Articles (AI)
AVERAGE	145.92	195.52	10.52	14.54	0.7	0	0.7	0	1.68	0	3.06	4.66	2.6	6.4	4.32	9.58
MEDIAN	155.5	199.5	11	15	1	0	1	0	2	0	3	4.5	2.5	7	4	10
STD	43.47452	10.39867	2.56539	0.973317	0.814411	0	0.646813	0	0.998775	0	1.268295	0.847806	1.293626	0.755929	1.406109	0.882714
MODE	178	200	12	15	0	0	1	0	1	0	3	4	3	7	4	10
MAX	241	205	15	16	3	0	2	0	4	0	6	8	6	8	8	11
MIN	48	160	4	12	0	0	0	0	0	0	1	4	0	5	2	7

The average word count produced by AI is 195.52, while the average word count produced by humans is 145.92. There is more fluctuation, as evidenced by the human word count standard deviation of 43.47. Conversely, AI's lower standard deviation (10.40) indicates that it generates more reliable findings. Humans can write 241 words, while AI can only write 205. The average number of sentences per text is 10.52, with a standard deviation of 2.57. AI generates 14.54 phrases on average, with a somewhat smaller standard deviation of 0.97. AI has a high preference for sentences of that length, with an average of 15 sentences.

People exhibit an overgeneralization trend in grammatical errors, with a mean score of 0.7 and a standard deviation of 0.81. AI has a score of 0 and no volatility. Similarly, humans score 0.7 with a standard deviation of 0.65 on omission errors, whereas AI scores zero. Misformation errors range from a maximum of 4 to an average of 1.68 for humans. AI is error-free. Human writing constantly demonstrates these patterns, but AI-generated writing completely lacks them.

The descriptive data additionally displays the use of various grammatical components. Humans use the past tense with a mean frequency of 3.06 and a standard deviation of 1.27, but AI uses it with a mean frequency of 6.79 and a lower standard deviation of 0.85. The human past tense mode is three; the AI mode is four.. For plural nouns, humans average 2.6 with a standard deviation of 1.29, but AI averages 6.4 with a standard deviation of 0.76. The mode for AI plurals is seven. The average usage of articles by AI is 9.58 with a standard deviation of 0.88, whereas the average usage of articles by humans is 4.32 with a standard deviation of 1.41. Certain grammatical traits are used more frequently and consistently by AI than by humans.

Research Question 2: How do the grammatical errors in AI-generated texts compare with those of EFL learners in terms of type, frequency, and distribution?

A comparative investigation of mistake types demonstrates that AI-generated texts differ from human writings in terms of error profile. Table 2 data shows that many mistake types frequent in human writing are completely missing in AI writing.

Table 2: Comparison – Human vs AI

Metric	Welch_t	p_value_t	MannWhitney_U	p_value_u	Human_mean	AI_mean
Word Count	-7.846045793	1.63E-10	278	2.06E-11	145.92	195.52
Sentence Count	-10.35988102	3.20E-15	137	7.86E-15	10.52	14.54
Overgeneralization	6.077701995	1.78E-07	1900	5.22E-09	0.7	0
Omission	7.652514333	6.52E-10	2000	1.10E-10	0.7	0
Misformation	11.89396689	4.68E-16	2400	3.29E-18	1.68	0
Frequency_PastTense	-16.90629828	1.41E-44	1671	5.42E-34	3.066666667	6.789443149
Frequency_Plural	-8.721508056	2.41E-14	648	9.19E-12	3.905167297	6.977777778
Frequency_Articles	-2.358993443	6.26E-02	92	4.26E-03	7.166666667	9.585035708

In terms of overgeneralization errors, human authors have an average rate of 0.7, but AI writings do not have any. In the category of omission errors, humans again have a mean rate of 0.7, but AI texts include no omissions. For misformation errors, the human mean is 1.68, with a maximum value of 4, whereas AI texts have a mean of 0. AI may completely prevent these sorts of linguistic errors.

In human writing, the past tense is used 3.06 times on average. AI-generated texts occur 4.66 times on average. AI prefers to use past tense formulations more often than human authors, maybe as a literary tactic. There is heterogeneity in the distribution of the noun usage data. The average frequency of singleton forms in human works is 2.6, while the average frequency of plural forms is 4.32. Compared to the average for humans, AI-generated texts employ plural forms more frequently (6.4). Human texts are more common than AI texts (4.32 vs. 9.58). AI-generated text is more meticulously organized and includes more specific details.

Research Question 3: To what degree do frequency and analogy shape the grammar of AI models when compared to human learners?

To comprehend the forces driving AI grammar, we must first consider the scope and significance of the differences between human and AI evolution. Usage-based theories assert that linguistic forms that appear more frequently in input become more ingrained in output. The results of inferential statistics support this claim. For example, the Welch's t-value of -16.906 and p-value of 1.41E-44 indicate a difference in past tense usage between humans (mean = 3.06) and AI (mean = 6.79). Given the high level of statistical significance, the divergence may not be random. The effect magnitude of this measure is classified as "Very Large." The frequency of past tense forms in the training data has a substantial effect on the AI's output. It may result in a far higher rate of utilization than that of humans.

The difference in plural noun usage between humans (mean = 2.60) and AI (mean = 6.40) is supported by a Mann-Whitney U value of 648 and a p-value of 9.19E-12. "Large" is the size of the impact. The increasing use of plural nouns is one recurring theme in AI literature. One possible contributing aspect is the use of plural forms in extensive text collections.

The error data can also be interpreted in terms of consumption. AI recorded zero points for overgeneralization, omission, and misformation errors, but humans receive positive means. These comparisons had high Welch's t-values (6.08, 7.65, and 11.89, respectively), as well as significant p-values ($p < 0.001$). Statistics show that misformation errors have a very big effect size. AI does not make errors. Human writers frequently produce such errors. In contrast, AI-generated output rarely contains incorrect forms, although human language does.

Human writing frequently contains errors. Overgeneralization is a common blunder. The average score for this mistake is 0.7. Humans reason through analogies. In a new scenario, humans may apply a previously learned grammar rule, an analogy-based learning process. AI does not commit these errors. This means that AI language is determined by the frequency of training data. AI does not appear to employ analogy in the same cognitive manner as humans. The study found that analogy is fundamental in human language. Frequency is the key to AI grammar.

Research Question 4: Can AI models be considered reliable instruments for exploring and testing usage-based theories of grammar?

The results of the statistical comparison show that AI models can be useful instruments for examining particular facets of usage-based theories. But it's important to recognize their limitations. The differences between the two writing styles are evident from the impact sizes shown in Table 3.

Table 3: Effect sizes for all metrics

METRIC	HUMAN MEAN	AI MEAN	DIRECTION (AI VS. HUMAN)	EFFECT SIZE STRENGTH	INTERPRETATION
WORD COUNT	145.92	195.52	AI > Human	Very Large	AI essays are much longer and consistently so.
SENTENCE COUNT	10.52	14.54	AI > Human	Very Large	AI essays contain more sentences across the board.
OVERGENERALIZATION	0.70	0	Human > AI	Large	Humans make these errors; AI almost never does.
OMISSION	0.70	0	Human > AI	Large	Humans drop elements (articles, auxiliaries); AI does not.
MISFORMATION	1.68	0	Human > AI	Extremely Large	Humans often form wrong grammatical shapes; AI essays are virtually error-free.
PAST TENSE	3.06	4.66	AI > Human	Very Large	AI strongly favors past tense verbs compared to humans.
PLURAL	2.60	6.40	AI > Human	Large	AI uses more plurals, often in general/abstract statements.
ARTICLE	4.32	9.58	AI > Human	Moderate–Large	AI uses more articles, though the difference is less pronounced than for other metrics.

Note: All comparisons are statistically significant ($p < 0.001$).

When researching usage-based grammar, AI models can offer a useful baseline or control condition. AI outputs are a pure kind of frequency-driven language generation since they are largely influenced by statistical frequencies in large datasets. Researchers can contrast this AI baseline with human writing, which is influenced by usage, analogy, and creativity. AI avoids typical mistakes. It enables researchers to distinguish between the characteristics of human writing that stem from frequency patterns in input and those that emerge from imperfect learning or creative analogy.

However, determining how AI differs from human cognition is essential to its validity as a tool. The foundation of use-based theory is that AI does not learn grammar through contextual social usage. It learns by identifying statistical patterns. The results imply that AI produces longer messages with more intricate structures, which could be the result of training data rather than a requirement for communication. Because of this, AI is dependable for testing theories about frequency effects. However, it might not be as trustworthy when studying the social and cognitive aspects of language use.

Discussion

The study's findings provide light on how AI-generated text differs from human writing in a number of ways. According to the results, AI often writes lengthier sentences than people. The way AI systems understand and generate language might be the cause of this output length disparity. AI models have free access to enormous datasets, in contrast to human writers who are constrained by cognitive limitations. The results align with previous studies on language complexity. Biber et al. (2011) claim that production conditions have a major impact on textual complexity. AI may provide more verbose content as it is not limited by real-time processing constraints.

Errors are an inevitable part of language development, according to usage-based theories. Youngsters pick up language by gradually deducing patterns from discrete samples (Tomasello, 2003). Overgeneralization occurs frequently while using this method. One common issue with this approach is overgeneralization. For instance, a child would say "goed" instead of "went." These mistakes demonstrate that the student is actively developing rules based on knowledge. The complete lack of mistakes of any kind in AI writing is one shocking discovery. Unlike AI, humans made mistakes by misrepresenting, omitting, and overgeneralizing data. This difference is very critical. AI does not learn via the same method of rule abstraction and creative application, as evidenced by the lack of analogous mistakes. Rather, AI appears to replicate statistically plausible sequences without the trial-and-error process that humans require to learn.

The increasing use of past tense forms and plural nouns by AI demonstrates how important frequency is in determining language output. Bybee (2006) showed that usage frequency has a major impact on language change and entrenchment. High-frequency phrases cause a speaker's internal grammar to become increasingly embedded. For AI taught on large corpora, the frequency of forms in the input predicts the frequency of forms in the output. The AI's output is consistent with the statistical distribution of the training data. This supports the notion that frequency effects do exist, but they act differently in cognitive learners like humans and statistical learners like artificial intelligence.

However, the fact that human writing contains misformation errors whereas AI does not shows a fundamental difference between the two systems. The use of language by humans is inherently creative. This is the creative side of language use, as defined by Chomsky (1965): the capacity to create and understand novel phrases. But there is a risk of error with this inventiveness. Humans experiment with language, make analogies, and sometimes generate new forms. Generalizing patterns from input is a necessary part of language acquisition (Goldberg,1995). Sometimes these generalizations are too general, which leads to errors. AI doesn't engage in these kinds of imaginative generalizations. It produces error-free but perhaps less creative language by repeating patterns it has observed.

Following Ellis (2008), language learning involves both a cognitive process of pattern identification and a social activity of interacting with others. AI lacks this social component. It does not convey meaning through language in the same way that people do. The comparison of human and artificial intelligence writing raises fundamental problems regarding the nature of linguistic knowledge. Usage-based theories hold that grammatical knowledge is learned through real language usage. Langacker (1987) claims that grammar is developed by the recurrent activation of linguistic patterns. The investigation's findings indicate that input patterns influence the AI's output. In this restricted sense, AI employs a usage-based approach. However, human grammar also encompasses abstraction, analogy, and social interaction.

Conclusions

Despite their limitations, AI models can be considered reliable tools for investigating usage-based grammar principles. The past tense and plural use have large impact sizes, implying that they may be used to investigate the impacts of frequency distributions on language development. They can also assist in establishing a standard for consistent, formal writing that is error-free. Researchers must include human data in AI studies in order to fully appreciate the analogical, creative, and social processes that usage-based theory seeks to describe. Combining AI and human analysis results in a more complete picture of grammatical comprehension.

The new study does, however, have a number of serious shortcomings. AI models are always evolving. Future studies may examine how AI language changes over time. These characteristics might be used by researchers to study the evolution of human language across time. Are models of artificial intelligence starting to resemble human writers more? The question is still unanswered. Additionally, the study only looked at the English language. Future studies may concentrate on multilingual AI writing. The patterns and structures of languages differ. Researchers might look at whether these differences are reflected in AI. Is it feasible for AI taught in Spanish, Arabic, or Japanese to detect traits unique to those languages?

This study only looked at one type of writing. Depending on the context and the goal, human language changes. Different linguistic qualities are used in different kinds of writings. Future studies could determine whether AI correctly alters its style. Does the writing style of AI vary based on whether it's a news item, a story, or a scientific report? The study also looked at grammar and word choice. Contextual meaning was not examined. Communication requires more than just perfect grammar. Future studies could determine whether AI-generated writings are suitable for their environment. Can AI tell the difference between succinct answers and in-depth justifications?

Nowadays, a lot of people use artificial intelligence as a writing tool. Future research could look into how this affects human language. Researchers may look into whether AI affects human writing. Does the writing style of AI users change over time? Does the use of AI make writing by AI more like writing by humans?

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