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Rethinking Interpreting Training: The Impact of Interpreting Mode on Learner Performance Through Entropy-Based Measures

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ABSTRACT

This study investigates the influence of interpreting mode on learner performance and its practical implications for interpreting training. Utilizing a corpus of learners' performance in Chinese-English consecutive interpreting (CI) and simultaneous interpreting (SI), this study applies two entropy-based measures, namely word entropy and part-of-speech (POS) entropy, to analyze the linguistic properties of learners' output and the cognitive processes involved. Results indicate that learners' output in CI demonstrates a lower level of lexical and syntactic complexity compared to SI, suggesting heightened cognitive saturation that motivates learners to rely on less complex linguistic constructs to manage increased cognitive load. These findings challenge the conventional sequential training approach, which advocates mastering CI before SI due to the latter's greater cognitive demands. A parallel training approach, which allows learners to have simultaneous engagement with both modes, may offer a more effective strategy for addressing the distinct cognitive challenges associated with each interpreting mode.

摘要

本研究调查了口译模式对学习者表现的影响及其对口译训练的实际意义。本研究利用学习者在汉英交替传译和同声传译中的表现语料库, 应用两种基于熵的测量方法, 即词熵和词性熵, 来分析学习者输出的的语言特性以及所涉及的认知过程。结果显示, 与同传相比, 学习者在交传中的输出在词汇和句法复杂性方面表现出较低的水平, 这表明较高的认知负荷促使学习者依赖较简单的语言结构来应对。这些发现挑战了同传口译模式下学习者的认知负荷更高的传统观念, 以及主张先掌握交传再学习同传的传统训练方法。本研究主张让学习者同时参与两种口译模式, 以应对每种口译模式所特有的认知挑战。

1 | Introduction

Recent research on interpreting studies continues to inform the decision-making process for curriculum development in the process of interpreting training, even though it may not mention pedagogical implications explicitly (Sawyer 2015). The development and outcomes of different training approaches are influenced by various contextual factors, distinct decision-making strategies, and educational guidelines that are specific to the local setting (Pöchhacker 2019). The content and structure of the curriculum are of critical importance as they directly determine the effectiveness of relevant training approaches.

Among the key considerations in curriculum design is the question of which interpreting mode learners should focus on first: consecutive interpreting (CI) or simultaneous interpreting (SI). In interpreting programs at major universities, the training typically begins with CI, followed by SI (Gile 2009; Yamada 2019). This sequence aligns with a fundamental principle of the Paris School approach (Pöchhacker 2016), which requires learners to achieve a high level of proficiency in CI before advancing to SI training. While the CI-first training approach has had a wide influence on interpreting curriculum design, there are differing viewpoints. According to Yamada (2019), it can also be beneficial to introduce SI to students at an early stage. The rationale is that early exposure to SI can better prepare learners for the multitasking and rapid processing abilities required in professional interpreting assignments. In addition, there is emerging evidence suggesting that CI may not necessarily be easier than SI. For instance, a corpus-based study of the syntactic complexity of different types of interpreting output by Liang et al. (2017) found that the syntactic complexity of CI output is lower than that of SI. This result could indicate that interpreters might opt for less complex syntactic structures to manage the cognitive load when faced with the challenges of CI. In fact, evolving cognitive science has contributed to the development of a parallel training approach that allows learners to have simultaneous engagement with both modes of interpreting from the beginning. This approach builds skills progressively and incrementally, emphasizing the importance of exposing learners to both CI and SI early on to foster a deeper understanding of the distinct cognitive demands inherent in each mode (Longley 1978; Francis 1989; Aarup 1993; Kalina 1994; Gile 2001; Setton and Dawrant 2016).

Notably, the emergence of different training approaches largely relates to researchers' and trainers' varying understandings of the distinction between CI and SI and their cognitive demands. However, existing studies on this distinction have not yet reached a definitive conclusion, often overlooking its pedagogical implications. To address this research gap, the present study aims to explore the difference between the two interpreting modes and their implications for understanding various training approaches. Following this introduction, Section 2 reviews relevant studies on existing interpreting training approaches and the distinction between CI and SI while also introducing entropy-based measures, a set of linguistic indicators used in this study to model the characteristics of CI and SI output. Section 3 presents the corpus utilized in this research and explains how the entropy indicators are calculated. Sections 4 and 5 report the findings and discuss their implications in light of existing literature. Section 6 concludes by summarizing the results and pointing out limitations.

2 | Literature Review

2.1 | Sequential Versus Parallel Training Approach

The effectiveness of a sequential versus parallel training approach continues to be debated in studies examining the effectiveness of interpreter training program design (e.g., Andres 2015; Gile 2001; Russell et al. 2010; Seleskovitch and Lederer 1989). Proponents of the sequential approach argue that the cognitive processes and necessary skills for CI and SI are essentially the same, but that SI tends to be more cognitively challenging. Therefore, the association of European Masters in Conference Interpreting (EMCI) adopted a sequential instruction approach in 2001, beginning with consecutive interpreting and sight translation in their curriculum before progressing to simultaneous interpreting (Sawyer 2015). Conversely, those who support a parallel approach believe that the cognitive processes for SI and CI are inherently distinct, requiring different strategies and skill sets that can be best developed through simultaneous exposure (Aarup 1993; Francis 1989; Gile 2001; Kalina 1994; Longley 1978). From this perspective, it may be beneficial for learners to study SI and CI concurrently rather than sequentially to develop the discrete skill sets required for each mode of interpreting.

The sequential approach to interpreter training was developed under the influence of the "Interpretive Theory" (Seleskovitch 1968). The interpretive school posits that the cognitive processes involved in CI and SI are essentially identical, as both modes of interpreting involve a similar set of tasks, including listening, comprehension, memorization, and reformulation. However, SI tends to be an accelerated and more compact form of CI, as simultaneous interpreters need to perform these cognitive tasks concurrently, leading to increased cognitive load for learners compared to CI (Déjean Le Féal 1997). Recognizing the intrinsic similarity in the underlying cognitive processes, as well as the greater challenge posed by SI, the Interpretive School advocates that learners can begin with CI, which allows for the discrete training and development of the necessary interpreting skills, such as listening and speaking. This helps to lay a solid foundation for the learner's subsequent training in the more advanced and cognitively demanding techniques of SI. The sequential training approach has since then generated a wide-ranging impact on conference interpreter training programs, ensuring a coherent and progressive educational framework.

On the other hand, questioning the very rationale that CI is a prerequisite for SI, some researchers promote the parallel training approach to address the unique cognitive demands of each interpreting mode. Francis (1989) and Kalina (1992, 1994) advocate for a parallel curriculum design, arguing that the cognitive processes and abilities for CI and SI are distinct and should be trained in parallel. They emphasize that CI relies on short-term memory, note-taking, and macro-level comprehension, while SI demands instantaneous memory, reasoning, and predictive skills. Gile (2016), building on his cognitive load model, further distinguishes CI's two-stage process from SI's overlapping cognitive functions. He argues that each mode requires tailored strategies and training approaches to optimize performance. Similarly, Longley (1978) and Aarup (1993) propose that SI training can enhance CI abilities. They suggest that the immediate and automatic response capabilities developed through SI practice can strengthen skills like quick note-taking and rapid organization of the target language in CI. At the same time, Aarup (1993) also warns that an overemphasis on CI may lead to cognitive habituation to delayed modes. This, in turn, could impede an interpreter's ability to adapt to the immediate cognitive demands of SI.

This ongoing debate underscores the complexity involved in designing effective curricula for interpreting training. However, the existing body of research on this topic remains limited in scope, highlighting the need for continued investigation into the impacts of different training approaches.

2.2 | Distinction Between CI and SI

Existing studies on the effectiveness of sequential and parallel approaches indicate that the underlying cognitive activities involved in different interpreting modes, along with the challenges faced by interpreters, are key factors to consider when designing curricula. Before delving deeper into the different impacts of the two training approaches, it is necessary to have a brief review of research that examines the distinction between CI and SI to understand the varying cognitive activities involved in the two modes of interpreting.

Departing from a process-oriented approach, one group of researchers is interested in unveiling the cognitive mechanism that underpins interpreters' real-time processing efforts in varying interpreting scenarios. A number of specific aspects of interpreting were studied, such as the practice of note-taking (Chen 2017, 2020; Dam 2004; Kuang and Zheng 2022), the interpreting of numbers (Frittella 2019), and syntactic processing approaches (Jiang and Jiang 2020; Wang and Liu 2019). Most of these studies rely on experimental designs to collect diverse behavioral data, eye movement data, and, more recently, physiological data to delineate the mental infrastructure of an interpreter's working memory, which is crucial for the achievement of adequate interpreting (Dong et al. 2019; Gile 2009; Lin et al. 2018; Shlesinger 2000; Van de Putte et al. 2018). While the process-oriented approach has the advantage of capturing the interpreter's real-time cognitive activities, most data are collected in an experimental setting, which may not truly reflect how interpreters perform in real scenarios.

Recognizing the limitations of the experimental approach, some researchers attempt to explore the characteristics of interpreting output and their reflection of the underlying cognitive process using corpus-based methods (Jiang and Jiang 2022; Kotze 2019; Liang et al. 2017; Lin and Liang 2023; Lv and Liang 2019; Shlesinger 1998; Xu and Liu 2023a). As the corporal data are collected from authentic interpreting activities, they help to ensure ecological validity, providing a more accurate representation of interpreter performance in real-world contexts (Setton 2011; Xu and Liu 2024). For instance, Xu and Liu (2023a) compared the syntactic complexity of interpreted and non-interpreted speech using dependency-based measures. It was found that interpreted speech tends to have a lower mean dependency distance, representing a lower level of syntactic complexity. The researchers argued that the use of more simplified syntactic structures may result from the interpreter's efforts to reduce the high cognitive load during the interpreting activity. Similarly, Jiang and Jiang (2022) adopted a corpus-based approach to study the application of the Menzerath—Altmann Law to analyze the output in CI and SI. The results reveal a greater tendency for interpreters to shorten clauses as sentence length increases, suggesting that SI imposes a higher cognitive load than CI. This finding largely confirms the effectiveness of using corpus-based methods to investigate the disparate language use representation in CI and SI, as well as how such representations are shaped by cognitive constraints.

2.3 | Entropy-Based Measurements

Understanding the fundamental cognitive processes involved in CI and SI is of utmost importance, as it sheds light on the efforts required by learners to develop competence in these two modes. This understanding can offer valuable insights to inform the design of interpreting curricula. In this study, we aim to gauge the cognitive demands placed on learners in both CI and SI by examining the linguistic property of their interpreting output as evidenced by entropy-based measurements.

Entropy, first used in thermodynamics in 1854 by T. Clausius, refers to the degree of disorder in a thermodynamic system. Shannon (1948, 1951) developed entropy into a measure of randomness and uncertainty in a text based on information theory. Information entropy can also be used as a measure to evaluate the complexity of a system. Theoretically, the more complex the system is, the higher the information entropy is, and vice versa. If a textual entity is viewed as a system, higher entropy values indicate that it carries more information content. Entropy-based measures have been widely applied to examine the level of linguistic complexity and informativeness in language use (Chen et al. 2017; Juola 2013; Liu 2016; Shi and Lei 2022). Given their effectiveness in quantifying the linguistic complexity of language output, which is a manifestation of processing efforts, entropy-based measures can also be used to examine the cognitive demands of various language activities (Hale 2003; Levy 2008). For example, under high cognitive load, language producers may rely on more simplified linguistic constructs to manage the increased demands (Lin and Liang 2023; Xu and Liu 2023a, 2023b). These simplified constructs result in lower entropy values, reflecting reduced linguistic complexity.

More recently, entropy-based measures have been used by researchers to examine the unique properties of translational language and the associated cognitive cost (Liu et al. 2022; Lin and Liang 2023; Liu and Cui 2024; Wang et al. 2024). For example, Liu et al. (2022) examined simplification in translation by comparing both lexical and syntactic complexity of translated and non-translated texts. It was found that translational Chinese is more simplified at the lexical level, as evidenced by the unigram entropy, but not at the syntactic level based on the part-of-speech entropy. In the same vein, Wang et al. (2024) used machine learning technology to classify translated and non-translated Chinese texts by calculating the entropy value of varying syntactic structures of these two language varieties. The results show that translated Chinese texts exhibit more complex syntactic constructs compared to non-translated texts, providing insights into the effects of translation on language syntax. With a focus on interpreted speech, Lin and Liang (2023) leveraged entropy and repeat rate measures to investigate the differences in informativeness and linguistic patterns between CI and SI outputs. The findings reveal that CI output is more heterogeneous when the source text is more linguistically complex. The authors point to an implication that CI represents a cognitive process that strikes a balance between production efficiency for interpreters and adequate comprehension for listeners, especially for more complex source speech. In addition, it was found that the informativeness of the source language has a significant influence on the informativeness of interpreting output. Lin and Liang's (2023) study shows the effectiveness of employing entropy-based analysis to investigate the characteristics of different interpreting modes. Its findings carry practical implications for the development of targeted training programs, enabling training institutions to tailor their curricula to address the specific cognitive challenges posed by each mode.

Against this research background, the present study sets out to investigate how interpreting mode affects learners' performance to reflect on its implications for interpreting training. Entropy-based measures will be used to compare authentic learners' interpreting output in CI and SI by modeling the level of linguistic complexity to reveal their performance and the underlying cognitive activities. Specifically, this study will address the following research questions.

1. How does the learners' output in CI and SI vary in terms of its level of complexity?
2. How do the potential variations indicate the underlying cognitive activities in CI and SI?

3 | Methodology and Material

3.1 | Corpus Design and Compilation

Setton (2011, 38) emphasizes the importance of using "authentic corpora", which refers to empirical data gathered from actual interpreting performance rather than relying on anecdotes, introspection, or experimental data. Departing from a product-oriented perspective, the present study adopts a corpus-based approach to examine the distinction between CI and SI and their respective cognitive demands on learners. To this end, this study compiled the Interpreting Learners Performance Corpus (ILPC). ILPC contains 23 learners' in-class interpreting performance over a training course of 13 weeks. The 23 learners were enrolled in a master's program in translation and interpreting at the Hong Kong Polytechnic University. All 23 learners are native Chinese speakers with high English proficiency. Specifically, ILPC consists of two sub-corpora: Learners CI Performance (LCIP) and Learners SI Performance (LSIP). LCIP includes the 23 learners' CI performance in 11 interpreting exercises. In each exercise, learners were asked to consecutively interpret a Chinese speech into English. Likewise, LSIP contains the same learners' SI renditions of Chinese speech in 11 interpreting exercises. The LCIP and LSIP were collected from recordings of a CI and an SI subject, respectively. The recordings were transcribed using iFLYTEK, an automatic transcription tool with over a 98% accuracy rate. A manual data cleaning was conducted to eliminate potential distracting features, such as non-English tokens, mispronunciations, and code-switching.

All the source speeches were delivered by top-level officials of the Chinese government at major international events. These speeches address topics about global security and development, such as the world economy, technological advancement, and international cooperation. This makes LCIP and LSIP comparable in terms of genre, formality, interpreting setting, and producer identity. In addition, to ensure the source texts used for each subject are at similar difficulty levels, dependency distance (Liu 2008), a reliable indicator of syntactic complexity and comprehension difficulty, was introduced to compare the syntactic complexity of the source text (ST) for CI and SI. An independent samples t-test shows that there is no significant difference in mean dependency distance between CI inputs ($MDD = 4.426$, $SD = 0.729$) and SI inputs ($MDD = 4.093$, $SD = 0.401$), with $t\text{-}value = 1.327$, $df = 20$, $p\text{-}value = 0.199$, and $d = 0.566$. The detailed information on the ILPC is summarized in Table 1 below.

TABLE 1 | Summary of Corpus.

Sub-corpora	Language	Text Count	Overall size	Mean text length
CI course	English (Target)	217	45762	210
	Chinese (source)	11	3661	332
SI course	English (Target)	229	44589	194
	Chinese (source)	11	3649	331

3.2 | Calculating POS Entropy and Word Entropy

All the transcribed and cleaned texts were imported in Spyder (Python 3.11) to conduct part-of-speech (POS) tagging to facilitate consequent calculation of the word entropy and POS entropy value of both source and interpreted speeches in the two interpreting modes. The word entropy value of a given sentence or text shows its lexical complexity because it quantifies the diversity and unpredictability of word choices (Liu et al. 2022; Zhu and Lei 2018). POS entropy captures the overall distribution and diversity of part-of-speech tags in the output. As the POS entropy reflects the density of the different grammatical units in a sentence, its value is widely used as an indicator of syntactic complexity (Chen et al. 2017; Murphy 2015; Wang et al. 2024). This study uses the Shannon's (1948) entropy formula as shown below:

$$H(X) = -\sum_{i=1}^{n} Pi \log bPi \tag{1}$$

In Formula (1), $H(X)$ means the information entropy of a random variable (X) representing the average uncertainty of (X), P_i is the probability of a certain type in the text, which is to calculate its relative frequency and $\log_n P_i$ takes the logarithm of the probability P_i based on b, reflecting the amount of information provided by the value i. The parameter b represents the base of the logarithm in the formula. When b equals 2, the unit of information is measured in bits. This is the most commonly used base in information theory, as it aligns with binary systems, which form the foundation of modern computing and digital communication (Shannon 1948). So, the entropy of a text is calculated by the sum of expected values for all types. Therefore, the combined formula employed in this study could be simply computed using Formula (2). Typically, one estimates the P_i values based on their relative frequency using Formula (3), where N is the total of all the frequencies in the text and f_i is the absolute frequency of unit i (Altmann and Köhler 2015).

$$H(X) = -\sum P_i \log_2 P_i \tag{2}$$

$$H(X) = -\left(\frac{2}{27}\log_2(\frac{2}{27}) + \frac{2}{27}\log_2(\frac{2}{27}) + \ldots + \frac{1}{27}\log_2(\frac{1}{27})\right) \approx 4.51 \text{ bits / word}$$

FIGURE 1 | Formula calculating word entropy of Example 1.

$$H(X) = -\left(\frac{9}{27}\log_2(\frac{9}{27}) + \frac{5}{27}\log_2(\frac{5}{27}) + \ldots + \frac{1}{27}\log_2(\frac{1}{27})\right) \approx 3.36 \text{ bits / word}$$

FIGURE 2 | Formula calculating POS entropy of Example 2.

$$P_i = \frac{f_i}{N} \quad (3)$$

For instance, to calculate the word entropy of the sentence in Example 1, we first count that there are 27 words in the sentence. Apart from "the," "solve," "and," "as," and "to" which appear twice, the rest of the words occur only once. Using Formula (2), the word entropy of the sentence is 4.51, as shown in Figure 1. To calculate the POS entropy of the same sentence, the number of each word type is counted, as shown in Example 2. Taking noun as an example, it appears nine times, contributing to the highest frequency. The POS entropy of this sentence is 3.36, as shown in Figure 2.

Example 1: China urges Haitian authorities to solve the disparity through negotiation, improve law administration and self-development to solve the current political crisis as soon as possible, and reform.

Example 2: China (noun) urges (verb). Haitian (noun) authorities (noun) to (particle) solve (verb) the (determiner) disparity (noun) through (adposition) negotiation (noun) improve (verb) law (noun) administration (noun) and (conjunction) self-development (noun) to (particle) solve (verb) the (determiner) current (adjective) political (adjective) crisis (noun) as (adverb) soon (adjective) as (conjunction) possible (adjective) and (conjunction) reform (verb).

4 | Results

4.1 | Word Entropy and POS Entropy Difference Between CI and SI Output

In order to explore the distinction between CI and SI output in terms of their complexity at lexical and syntactic levels, word entropy and the POS entropy of each interpreted speech are calculated. The mean word entropy and POS entropy values of CI and SI output across the 23 learners' performance are presented in Table 2. The results show that the mean word entropy value of CI output (M = 6.237, SD = 0.148) is lower than that of SI (M = 6.437, SD = 0.125). As for the POS entropy, the mean value of CI output (M = 2.701, SD = 0.168) seems to be close to that of SI (M = 2.754, SD = 0.079) with the former being slightly lower than that of the latter. At the same time, it is interesting to note that the CI output exhibits a much wider range of POS entropy values, with a noticeably higher standard deviation compared to SI output. To determine whether the observed difference has statistical significance, two simple t-tests were conducted. As shown in Figure 3, CI output differs from SI output significantly in terms of their word entropy (t = −15.3768, df = 444, $p < 0.01$). While the difference in POS entropy has statistical significance (t = −4.2256, df = 444, $p < 0.01$), the magnitude of the difference is very modest. These findings show that CI output features a lower level of lexical complexity than that of SI. As for syntactic complexity, the output of the two interpreting modes seems to be at the same level.

TABLE 2 | Word entropy and POS entropy value across types.

	Word entropy			POS entropy		
	Mean	**SD**	**Median**	**Mean**	**SD**	**Median**
CI	6.237	0.148	6.245	2.701	0.168	2.723
SI	6.437	0.125	6.428	2.754	0.079	2.735

To further verify the statistical difference between CI and SI with respect to their word entropy and POS entropy, a classification model was applied to determine whether the two entropy-based measures can distinguish the two types of interpreting output (Tay 2024). The study looped over different values of k-Nearest Neighbors (k-NN), fit the model, and computed the accuracy. The best accuracy is 0.821 with k-NN = 2. A confusion matrix is generated, positioning all the CI and SI output in a two-dimensional space using their word entropy value and POS entropy value. The results show that the predictive accuracy for CI is estimated at 48.65%, whereas for SI, it stands at 33.41%. Furthermore, the misclassification rate of SI as CI is only 17.94%, suggesting that the two entropic indicators can effectively differentiate between the learners' output in the two interpreting modes. Interestingly, there were no false negatives of CI, implying that CI has more distinctive features than SI in terms of the two entropic indicators. (Figure 4).

4.2 | The Impact of Source Speech

Previous research has shown that the production of interpreted speech is constantly under the source language influence (Bacigalupe 2010; Liang et al., 2017, 2019; Lv and Liang 2019). This is because interpreting activity involves considerable bilingual language processing, which means interpreters need to activate two language systems to comprehend the source language and produce an idiomatic rendition in the

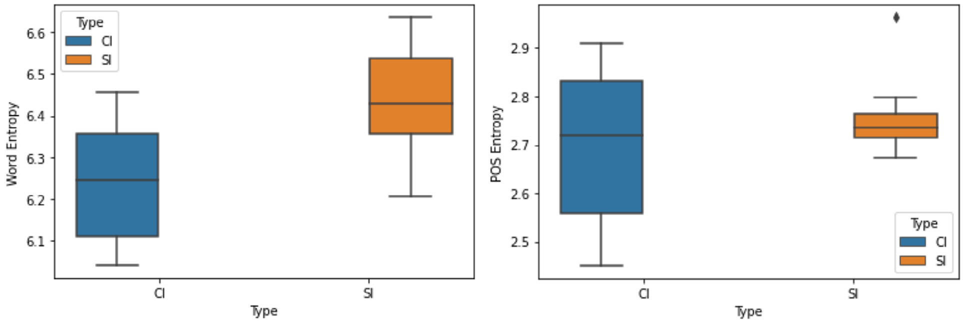

FIGURE 3 | Boxplots of word entropy (Left) and POS entropy (Right) value by interpreting mode.

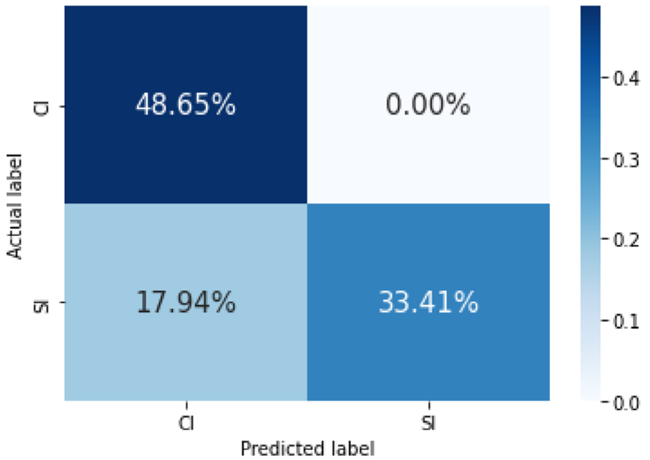

FIGURE 4 | Heatmap with percentages (rows = actual labels, columns = predicted labels).

target language (Ma and Cheung 2020; Xu and Liu 2024). In this process, interpreted speech may exhibit certain linguistic features or patterns that typify the source language, a phenomenon often referred to as shining through. The concept of shining through in translation studies indicates the influence of the source language on the translated text, causing it to lean towards the linguistic and stylistic features of the original language (Teich 2003). In this study, while we have controlled the task difficulty of the interpreting exercise, the observed lexical and syntactic complexity in CI and SI outputs may be attributed to the linguistic characteristics of the source language. In order to examine the potential impact of source language on the manifestation of lexical and syntactic properties in interpreted speech, this study applied two multiple linear regression models (Norouzian and Plonsky 2018) to compare CI and SI output in terms of word entropy and POS entropy, respectively, while taking into consideration the source language influence, the impact of interpreting mode, and the interaction between these two factors.

In the first model, the word entropy of the interpreting output is set as the dependent variable, and the word entropy of source speech, interpreting mode (either CI or SI), and the combined effect between these factors are independent variables or fixed effects. The results reveal that interpreting mode and the combined effect of interpreting mode and source speech have statistically significant ($p < 0.05$) impacts on the word entropy of interpreting out. However, no such impact was found for source speech alone. This is shown in Table 3. In addition, it was found that when holding the source speech word entropy constant, SI output tends to yield higher word entropy values than CI. This is shown in Figure 5. These findings suggest that source speech has a limited impact on the manifestation of the lexical property of interpreting output. Instead, the variation of the word entropy value between CI and SI is mostly attributable to the interpreting mode.

TABLE 3 | Model 1 OLS regression results with combined predictors (*R-squared* = 0.507).

Predictor	coef	std err	t	$p > \|t\|$
Intercept	7.457	1.005	7.423	0.000
Interpreting Mode	−3.3940	1.570	−2.162	0.044
ST Word Entropy	−0.1939	0.160	−1.215	0.240
Interpreting Mode × ST Word Entropy	0.5727	0.250	2.289	0.034

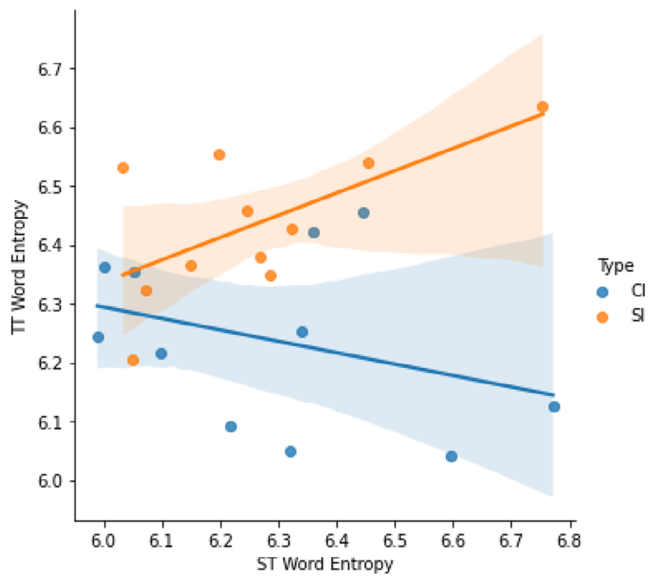

FIGURE 5 | Regression of interpreting output word entropy by source speech and mode.

In the second model, the POS entropy of the interpreting output is the dependent variable, while the POS entropy of source speech, interpreting mode, and the combined effect between these factors

TABLE 4 | Model 2 OLS Regression Results with combined predictors (*R-squared* = 0.338).

Predictor	coef	std err	t	*p* > |t|
Intercept	4.588	0.676	6.785	0.000
Interpreting Mode	−0.796	2.285	−0.349	0.731
ST POS Entropy	−0.546	0.195	−2.794	0.012
Interpreting Mode × ST POS Entropy	0.257	0.638	0.403	0.692

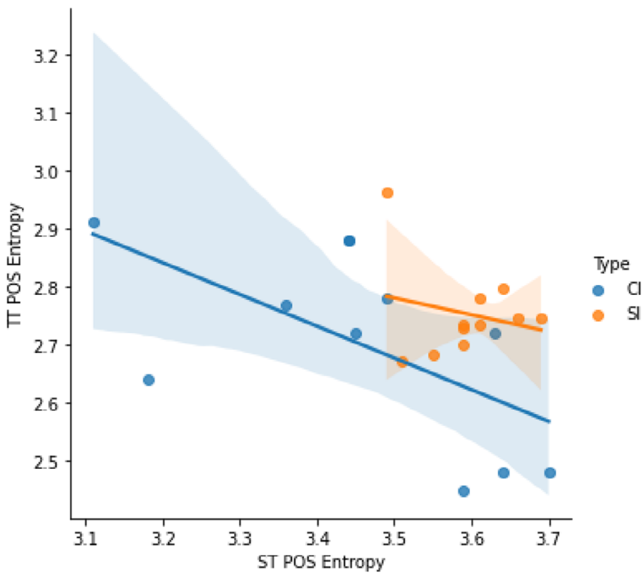

FIGURE 6 | Regression of interpreting output POS entropy by source speech and mode.

are independent variables. As shown in Table 4, the impact of interpreting mode and the combined effect of interpreting mode and source speech are not significant, whereas source speech has a statistically significant impact on the formation of the syntactic property of interpreting output. This finding suggests that the variation of syntactic property between CI and SI output is related to source speech. Therefore, the observed high standard deviation of CI output in terms of POS entropy value results from the wide range of POS entropy values of source speech. This can be shown in Figure 5, where the POS entropy value of the source speech of CI (blue line) covers a wider range in the x-axis. In addition, it was found that when holding the source speech constant, the SI tends to yield a higher POS entropy value than CI. This finding indicates that when the syntactic complexity of the source speech is controlled, SI output tends to have more complex syntactic structures than that of CI. This is shown in Figure 6.

5 | Discussion

5.1 | Simplification and Cognitive Demands

Generating data from a corpus consisting of interpreting learners' CI and SI output, this study explored how interpreting mode affects learners' performance to reflect on its implications for interpreting training. Two entropy-based measures, namely word entropy and POS entropy, were used to map the lexical and syntactic properties of interpreting output to reveal underlying cognitive activities. The findings reveal that learners' output in the two interpreting modes demonstrates varying lexical and syntactic patterns. Specifically, the CI output features reduced word entropy values and POS entropy values compared to SI output. Apart from the interpreting mode, the observed variation can also be attributable to the presence of source language influence, which complies with Lin and Liang's study (2023). Yet, it is interesting to find that source language has a statistically significant influence on POS entropy values but not on word entropy values. This suggests that when producing renditions, interpreters are more likely to be constrained by the syntactic structures rather than the lexical options of the source language. This is understandable given that, reformulating the syntactic structures may pose a higher cognitive demand on interpreters (Ma and Li 2021). Therefore, interpreters may use some of the syntactic structures of the source language directly to alleviate cognitive load. This result also indicates source language influence may have varying manifestations at different linguistic levels of the interpreting output, contributing to previous research on interference in the translational language (e.g., Dai and Xiao 2011; Lapshinova-Koltunski 2022; Xu and Liu 2024). Yet, when the source language influence is controlled, the CI output still demonstrates a tendency towards lexical and syntactic simplification, as evidenced by lower levels of word entropy and POS entropy values than those of SI. These results suggest that interpreting learners tend to rely on more simplified lexical options and grammatical structures in CI compared to their practice in SI (Bernardini et al. 2016; Laviosa 1997, 1998a, 1998b; Lv and Liang 2019).

Previous studies have shown that the linguistic characteristics of a text, such as its lexical and syntactic features, reflect the cognitive processes involved (Liang et al. 2017; Jia and Liang 2020; Lv and Liang 2019; Lin and Liang 2023). Based on the least effort theory (Zipf 1949), interpreters may rely on simplified linguistic constructs to alleviate high cognitive load. Therefore, the manifestation of simplification, that is, a decrease in linguistic complexity, is often indicative of a high cognitive load in the context of interpreting (Lv and Liang 2019; Xu and Liu 2023a, 2023b). Seen from this perspective, the reduced lexical and syntactic complexity observed in CI output may indicate a higher cognitive load experienced by learners in this interpreting mode, which motivates them to simplify their output to a greater extent. This result contravenes the conventional notion that SI is more cognitively demanding than CI because SI involves the simultaneous processing of incoming speech and output, which requires greater multitasking abilities and quick decision-making (Lv and Liang 2019). However, this perspective may overlook the intensive memory demands inherent in CI. Consecutive interpreters need to comprehend and internalize a relatively long chunk of the speaker's message before reformulating it in the target language (Gile 2009). This process involves not only understanding the content but also retaining key information and linguistic structures, which can place significant strain on working memory, even with note-taking. This finding is consistent with what was found in Liang and colleagues' (2017) study, where they compared dependency distance, a measure of syntactic complexity, across the output of CI, SI and translation output by professional interpreters. The results show that CI has the shortest dependency distance, indicating a lower level of syntactic complexity, followed by SI and translation. Similarly, in another study that compared the lexical complexity between CI and SI, Jia and Liang (2020) revealed that there was reduced use of adjectives in CI, which could be a result of underestimated cognitive demands placed on consecutive interpreters. In addition, the present study provides an interesting contrast to Lin and Liang's (2023) research, which found that CI was more informative and heterogeneous than SI when the source speech was more complex. These differing results may stem from the fact that the current study examines learners' performance in a classroom setting, while Lin and Liang (2023) focused on the output of professional interpreters in high-stakes conferences. CI may present greater challenges for learners due to their limited professional competence compared to professional interpreters. Furthermore, these findings suggest that the impact of modes on an interpreter's performance may be influenced by the interpreter's qualifications and experience.

5.2 | Implications for Interpreting Training

The preceding discussion on the cognitive challenges inherent in the distinct processes of CI and SI has practical implications for interpreting training. The findings of this study suggest that the sequential approach to interpreter training may need to be reevaluated. Conventionally, this approach advocates starting with CI before progressing to SI, based on the perception that SI is a more cognitively demanding activity (De Groot 2000; Meuleman and Van Besien 2009; Seeber 2013). However, our findings challenge this assumption by indicating that CI imposes greater cognitive demands on learners, primarily due to the extensive memory retention and reformulation tasks required during this mode. Considering the varying cognitive mechanisms of the two interpreting modes (Gile 2009) and the observation that SI is less cognitively demanding, the present study largely supports Yamada's (2019) results, which indicate that SI may be introduced earlier to help develop multitasking and rapid processing abilities. These findings contest the rationale for the CI-first approach, as the belief that CI serves as a preparatory step for SI may overlook the distinct cognitive processes involved in each mode. In fact, CI may present unique challenges that can be more taxing for learners than previously thought. Conversely, our findings align more closely with the parallel approach to training, which advocates for concurrent instruction in both CI and SI. This approach recognizes that the cognitive processes involved in each mode are different, suggesting that learners could benefit from exposure to both modes of interpreting from an earlier stage in their training (Gile 2001; Kalina 1992, 1994; Setton and Dawrant 2016). Given that CI tends to place high cognitive demands on interpreters, this integrated training method could equip learners with a more comprehensive skill set. Training students in both CI and SI simultaneously allows them to develop strategies that enhance cognitive flexibility and adaptability, which are crucial for navigating the diverse challenges posed by each interpreting mode or modality (Lv and Liang 2019). By fostering a diverse repertoire of skills, a parallel training approach not only prepares learners to handle the complexities of interpreting but also cultivates their ability to switch between different cognitive demands fluidly.

6 | Conclusion

This study utilizes entropy-based measures to examine how interpreting mode influences learners' performance and the practical implications for interpreting training. The quantitative analysis of lexical and syntactic complexity in learners' output in CI and SI provides valuable insights into the cognitive load associated with each mode. A higher cognitive load was observed in CI, as indicated by lower word and POS entropy. In contrast, learners' output in SI demonstrated greater lexical and syntactic complexity, suggesting reduced cognitive strain. This finding does not support the conventional sequential training approach that advocates learners to study CI first, based on the assumption that it is less cognitively demanding. Instead, it highlights the necessity of a training approach that adequately prepares interpreters for the specific cognitive challenges inherent in each mode. A parallel training approach that integrates both CI and SI from the outset offers a balanced foundation in language proficiency and complex information management. This strategy not only recognizes the distinct cognitive processes involved in each mode but also equips interpreters to effectively navigate the unique challenges they will face in professional settings.

The present study was among the first to apply entropy-based measures to study learners' interpreting performance and generate pedagogical implications by quantitatively modeling the linguistic properties of CI and SI output. This approach not only advances the methodological toolkit available for researchers to model the linguistic characteristics of interpreting output but also offers new insights into the cognitive processes involved in language processing during interpreting. Despite its innovation, this study has certain limitations due to its focus on a single genre, one direction of interpretation, and a specific language pair, which may impact the generalizability of the findings. To enhance future research, it would be interesting to incorporate retrospective interviews with participants to validate their performance assessments and strengthen the overall validity of the results. Additionally, employing a diverse range of statistical metrics could provide a more comprehensive analysis of the linguistic complexity of interpretations. Exploring additional language pairs or investigating the reverse direction of interpreting would also contribute to a deeper understanding of these phenomena.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data for this research has not been made public, but it can be obtained from the authors if you request.

Peer Review

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