A Quantitative Study of Syntactic Complexity across Genres: Dependency Distance in English and Chinese

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Abstract

This study investigates syntactic complexity in fiction and news genres by analyzing mean dependency distances (MDD) across controlled sentence lengths in English and Chinese corpora. Results show that English fiction exhibits greater MDD than news, while Chinese fiction shows the reverse. More complex syntactic structures, i.e., complex coordination structures, are found in English fiction texts than in news writing. In contrast, Chinese news writing relies more on nominal modification and prepositional phrases that create long-distance dependencies than fiction texts. These findings show deviations from uniform correlations between genre formality and syntactic complexity across languages.

1 Introduction

Syntactic complexity of genres has been given explicit attention in the field of quantitative syntax (Biber & Conrad, 2019). Measurements, such as dependency distance and sentence length, have been employed to compare genres' syntactic difficulty (Oya, 2011; Wang & Liu, 2017, 2022; Chen & Kubát, 2024). Dependency distance, based on the concept of dependency grammar which describes the asymmetric syntactic relationship between two words concerned, refers to the linear distance between the governor and the dependent (Liu, 2008; Liu et al., 2017).

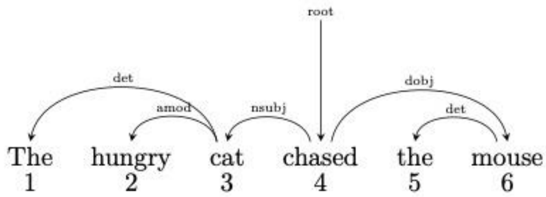

Figure 1: Dependency analysis of an example sentence.

For example, in the pair (*cat*, *chased*) in Figure 1, *chased* is the governor and *cat* the dependent, the type shown as the label above the arc is *nsubj* (nominal subject). The dependency distance of this pair is |3 – 4| = 1. The notion of dependency distance signals the difficulty level of a given sentence. The greater the dependency distance, the more difficult the syntactic analysis of a sentence is (Gibson, 1998; Liu et al., 2017).

Recent advances in quantitative dependency syntax (Futrell et al., 2020; Yadav et al., 2022) have established more complicated frameworks for cross-linguistic analysis. These developments raise further questions about how dependency distance interacts with genre characteristics. Formal genres, such as informative texts, are presumably expected to have greater syntactic complexity, shown as the longer sentences and greater dependency distances. However, as investigated by Wang & Liu (2017), when sentence lengths are controlled, imaginative texts show greater dependency distances, which indicates more complex syntactic structures than do informative texts. They did not further conduct the statistical analysis of the descriptive statistics though, thus leaving questions regarding statistical significance unresolved. More recently, Chen & Kubát (2024) found that short stories in Czech National Corpus have greater dependency distances than newspapers, to some extent challenging the assumption that more formal texts

Proceedings of the Third Workshop on Quantitative Syntax (QUASY, SyntaxFest 2025), pages 39–46

necessarily contain more syntactically difficult sentences. Wang (2020) found that Chinese news' dependency distances are greater than fiction, albeit without controlling sentence lengths. These findings suggest that the relationship between genre formality and syntactic complexity warrants deeper investigation.

Thus, the present study intends to explore mean dependency distances of genres within controlled sentence lengths, with corpora from both English and Chinese. Research questions are as follows:

1) Do fiction genres demonstrate greater syntactic complexity than news genres when sentence length is controlled, and is this pattern language-specific or a cross-linguistic phenomenon?

2) Which dependency types, taking into account of both mean dependency distances and frequencies, contribute most to the observed patterns across genres and languages?

2 Methods and Materials

Texts in the English corpus were collected from FLOB corpus. FLOB (Freiburg-LOB Corpus of British English) is a British written English corpus, mainly including 15 genres. This paper extracted three types of news and three types of fiction genres, specifically including press reportage (A), press editorials (B), press review (C), general fiction (K), mystery and detective fiction (L), and humor (R). Ten texts are collected from each genre (except for humor fiction, which only has 9 texts in the corpus), resulting in a total of 59 English texts.

To ease English-Chinese register comparison, the Chinese corpus in this paper uses the Lancaster Corpus of Mandarin Chinese (LCMC), which was designed as a Chinese counterpart to the FLOB corpus following similar sampling principles and genre categories. Consistent with the English selection, this paper selected six Chinese genres—A, B, C, K, L, and R—comprising three news registers and three fiction registers, for a total of 59 Chinese texts.

According to the previous experience (Wang & Liu, 2017), the sentences from each text were grouped by length ranges from 1-5 words, 6-10 words, etc., as shown in Table 1. To ensure reliable statistical comparison, the present study primarily focuses on ranges up to 36-40 words, where each range contains at least 10 sentences in each genre and 200 sentences in all genres within one language. Detailed sentence counts for each genre after the data extraction are provided in Appendix A due to space limitations.

Length Range of English genres	Sent. Count	Length Range of Chinese genres	Sent. Count
1-5	936	1-5	375
6-10	1574	6-10	826
11-15	1288	11-15	1000
16-20	952	16-20	882
21-25	777	21-25	756
26-30	558	26-30	510
31-35	397	31-35	311
36-40	278	36-40	232
41-45	202	41-45	150
46-50	109	46-50	99
51-55	61	51-55	77
56-60	41	56-60	37
61-65	24	61-65	20
66-70	12	66-70	17
71-75	11	71-75	7
76-80	4	76-80	9
81-85	5	81-85	6
86-90	2	86-90	7
91-95	1	91-95	2
96-100	1	96-100	3
126-130	1	101-105	1
136-140	1	111-115	1

Table 1: Sentence count in English and Chinese genres.

Following the data extraction process, the Stanford parser (De Marneffe & Manning, 2008) (version 3.9) was employed to output the typed-dependency relations. Due to the relatively low accuracy rate of Stanford parser for Chinese, the current research, manually modified the parsed Chinese treebank.

In measuring the dependency distance of a sentence and of a sample, i.e., a large corpus, Liu et al., (2009) propose several methods. Let $W_1 \ldots W_i \ldots W_n$ be a word string. For any dependency relation between the words W_a and W_b ($1 \leq a \leq b \leq n$), suppose W_a is a governor and W_b is its dependent. The dependency distance (hereafter referred to as DD) between them is defined as their difference, i.e., $|a-b|$. The mean dependency distance (hereafter referred to as MDD) of an entire sentence can be calculated as the average of dependency distances. For instance, MDD of the example sentence in Figure 1 is (2+1+1+2+1) / 5 = 1.4. In the current research, to analyze sentences of similar lengths across different genres, the author calculated the MDD for groups of sentences (similar to a small corpus) within specific length ranges. The MDD of a corpus can be defined as:

$$MDD = \frac{1}{n-s}\sum_{i=1}^{n-s}|DD_i| \tag{1}$$

Here n is the total number of words, s is the total number of sentences and DD_i is the DD of the i-th syntactic link of the sample.

When the dependency type was investigated, two features, i.e., their dependency distances and frequencies were considered. The present study quantified those two factors by calculating the relative contribution of MDDs of each dependency type. Here is the formula for calculating relative contribution of each dependency type:

Raw Contribution = *Proportion* × MDD_{type} (2)

where *Proportion* is the dependency type's frequency relative to all dependencies in the corpus, and MDD_{type} is the mean dependency distance for that specific dependency type.

Relative Contribution (%) = *(Raw Contribution / Total* MDD_{corpus}*)* × *100* (3)

where *Total* MDD_{corpus} is the overall mean dependency distance across all dependency types in the corpus. This normalizes contributions as percentages of overall MDD, allowing for direct comparison across different dependency types and corpora.

3 Results and Discussion

3.1 MDD distribution

The distribution of MDDs across different sentence length ranges in English and Chinese genres is displayed in Appendix A and Figure 2 and Figure 3. Figure 2a and Figure 3a show the average MDD deviation from the overall MDD. Figure 2b and Figure 3b shows deviation of each genre's MDD from the overall average across all genres, with red showing positive deviation (higher than average MDD) and blue showing negative deviation (lower than average MDD).

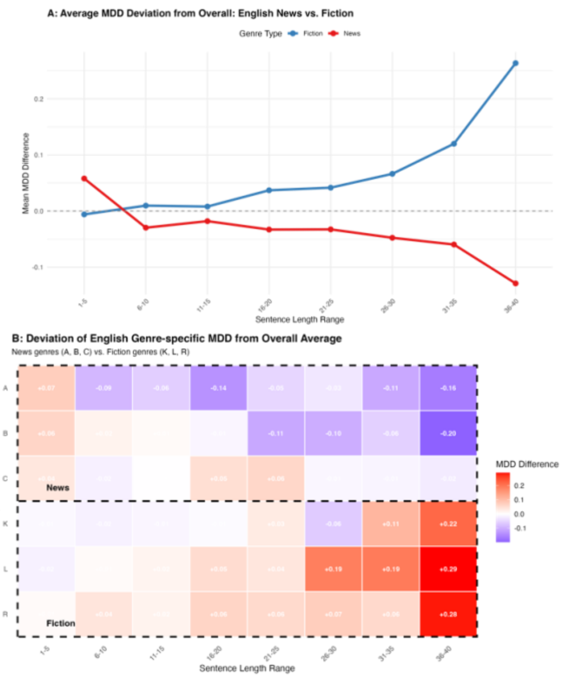

Figure 2: MDD distribution in English fiction and news

As shown in Figure 2, the gap between English fiction and news becomes greater as sentence length increases, with the maximum difference occurring in the 36–40 word range. Fiction (represented by genres K, L, and R) starts slightly below average for the shortest sentences but then rises above average as sentence length increases. For instance, genre R (humor) exhibits the most obvious positive deviation in the 36-40 word ranges. News (as shown by genres A, B, C) begins above average for very short sentences (1-5 words) but quickly falls below average and continues to decrease relative to the overall mean. Genre A (press reportage) showing the most consistent negative deviation across almost all length ranges.

As shown in Figure 3 and Appendix A, Chinese fiction and news texts display a different pattern from English genres. Chinese news genres (A, B, C) generally maintain above-average MDD across nearly all sentence length ranges, with slightly negative deviations in genre A (press reportage). Chinese fiction genres (K, L, R) generally display below-average MDD values. This pattern is reversed from what is shown in English, where fiction texts trend toward higher-than-average MDD in longer sentences.

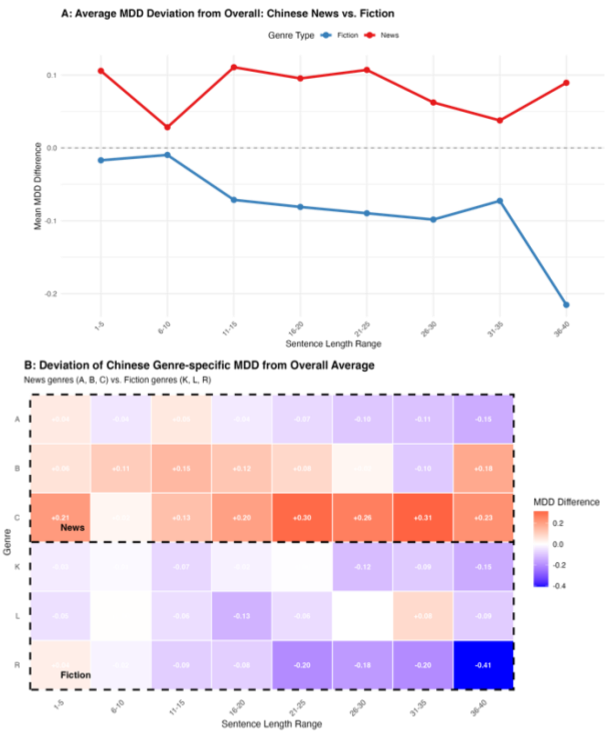

Figure 3: MDD distribution in Chinese fiction and news

A linear model was then fitted to examine the relationship between MDD, sentence length, genre, and language[1]. The model result of predicting MDD from the interaction of language, i.e., English and Chinese, genre type, i.e., news or fiction, and sentence length range, i.e., the average value of the sentence length range, shows an excellent fit with an R^2 value of 0.958 (F (7,88) = 289.03, $p < 0.001$).

Above all, there is a marginal significant main effect of language ($p = 0.06$), indicating differences in MDD between English and Chinese texts are marginally significant. Further, sentence length shows a highly significant main effect ($p < 0.001$), confirming that MDD consistently increases with sentence length across languages and genres. This confirms the previous finding that dependency distances are more optimized in English than in Chinese (Ferrer-I-Cancho et al., 2022).

The two-way interaction between genre and length range is not significant ($p = 0.31$), indicating that the relationship between sentence length and MDD is consistent across different genres when not considering language differences. However, the three-way interaction between language, genre type, and sentence length range is significant (F (1,88) = 6.83, $p = 0.01$). This interaction confirms the observation that the relationship between genre and sentence length differs significantly between English and Chinese.

The model coefficients support this interpretation as well. For Chinese fiction (the reference level), the coefficient for sentence length range was 0.060 ($p < 0.001$), indicating a strong positive relationship between sentence length and MDD. The interaction between language and length is also significant ($p = 0.02$), with a negative coefficient (-0.009), suggesting that sentence length has a different effect on MDD in English compared to Chinese. Further, the interaction between language, genre type, and sentence length range had a significant negative coefficient (-0.014, $p = 0.01$), demonstrating that the genre difference in how MDD changes with increasing sentence length is significantly different between languages.

3.2 Distribution of dependency types

To understand the underlying causes why these MDD differences emerge in Chinese and English, a detailed analysis of dependency types in longer sentences (ranges 21-25, 26-30, 31-35, and 36-40 words) was conducted. This analysis involved calculating both the MDDs and frequencies of various dependency types across these sentence lengths.

[1] The current research chose a standard linear model rather than a mixed-effects model based on a comparative analysis of both approaches. The random effects in the initial mixed-effects model (with random intercepts for genre nested within language, i.e., K, L, R, A, B, C) accounted for only 7.48% of the total variance, with a random intercept variance of 0.001486 compared to a residual variance of 0.018384. The improvement in explanatory power was minimal, with the R^2 increasing only from 0.9587 (fixed effects only) to 0.9618 (with random effects) – a mere 0.32% improvement. These statistics indicate that the simpler linear model provides equivalent explanatory power. Besides, due to small sample size in each genre, i.e., eight observations, as a random effect, the present study chose the linear model to avoid potential overfitting and to ensure more reliable parameter estimates.

Genre	Dep. Type	Prop.	MDD	Rel. Contribution
News	*prep*	0.125	2.66	12.14
News	*pobj*	0.119	2.24	9.74
News	*nsubj*	0.081	3.09	9.07
News	*conj*	0.036	6.96	9.02
News	*det*	0.106	1.67	6.43
News	*cc*	0.034	5.08	6.39
News	*ccomp*	0.016	7.95	4.65
Fiction	*conj*	0.042	8.18	12.04
Fiction	*prep*	0.106	2.48	9.18
Fiction	*cc*	0.042	6	8.76
Fiction	*nsubj*	0.108	2.13	8.07
Fiction	*pobj*	0.102	2.06	7.32
Fiction	*ccomp*	0.022	7.28	5.48
Fiction	*det*	0.099	1.53	5.29

Table 2 Top seven contributing dependency types in English genres.

Genre	Dep. Type	Prop.	MDD	Rel. Contribution
News	*conj*	0.088	8.62	21.38
News	*dobj*	0.088	3.77	9.38
News	*prep*	0.046	7.12	9.24
News	*nsubj*	0.089	3.27	8.25
News	*advmod*	0.088 6	2.78	6.95
News	*nn*	0.128	1.6	5.77
News	*ccomp*	0.03	5.5	4.66
Fiction	*conj*	0.104	10.07	31.61
Fiction	*nsubj*	0.122	2.68	9.87
Fiction	*advmod*	0.110	2.34	7.77
Fiction	*dobj*	0.085	2.84	7.27
Fiction	*ccomp*	0.052	4.42	6.87
Fiction	*prep*	0.039	4.96	5.84
Fiction	*nn*	0.055	1.49	2.47

Table 3 Top seven contributing dependency types in English genres.

Table 2 and Table 3 present the seven dependency types that contribute most significantly to the overall MDD in news and fiction genres for Chinese and English, respectively. In English, fiction texts show more complex coordination structures than news, with conjunctions (*conj*) having greater MDD (8.18 vs. 6.96) and higher frequency (0.042 vs 0.036) and coordinating conjunctions (*cc*) showing both higher frequency (0.042 vs. 0.034) and MDD (6.00 vs. 5.08). These patterns, to some degree, explain why English fiction demonstrates greater overall MDD than news.

In Chinese, the pattern differs. While conjunctions in fiction have higher MDD (10.07 vs. 8.62) and frequency (0.104 vs. 0.088) than in news, Chinese news writing shows greater complexity in other structures. Prepositional phrases (*prep*) in news have greater MDD (7.12 vs. 4.96) and higher frequency (0.046 vs. 0.039). Direct objects (*dobj*) show similar frequency across genres but higher MDD in news (3.77 vs. 2.84). News writing also employs extensive nominal modification (*nn*: 0.128 vs 0.055), which partly contributes to information density. These patterns likely contribute to Chinese news having higher overall MDD than fiction.

3.3 Discussion

The present study reveals a clear cross-linguistic divergence in the relationship between genre and syntactic complexity, as measured by mean dependency distance (MDD). In English, fiction genres demonstrate higher MDD values than news genres when sentence length is controlled. In contrast, Chinese shows the opposite pattern: news genres exhibit greater MDD values than fiction. These findings deviate from the assumption that syntactic complexity correlates with genre formality across languages. The English findings align with Wang & Liu's (2017) observation that when sentence lengths are controlled, imaginative texts show greater dependency distances, which indicates more complex syntactic structures than do informative texts. Furthermore, the present study provides the statistical significance test that Wang & Liu (2017) acknowledged was missing from their work, demonstrating that these differences are indeed statistically significant ($p < 0.01$). These findings also complement Chen & Kubát's (2024) work on Czech, which found that short stories in Czech National Corpus have greater dependency distances than newspapers. This supports that more formal texts do not necessarily contain more syntactically difficult sentences across all languages.

In English, the higher MDD in fiction genres is to some degree driven by the prevalence of complex coordination. Specifically, dependency types such as *conj* and *cc* have greater distances and higher frequencies in fiction than in news, contributing the most to overall MDD. This suggests that English fiction frequently employs longer-range syntactic dependencies, likely reflecting narrative style and the use of more elaborated clause structures. This distinction is consistent with prior observations that formal English writing often emphasizes phrasal over clausal elaboration (Biber & Gray, 2010).

In Chinese, the pattern reverses: news genres produce greater MDD values than fiction. This is shown by the syntactic features of Chinese news writing, which often include extensive nominal modification and prepositional phrases that introduce long-distance dependencies. For example, *prep*, *dobj*, and *nn* dependencies in Chinese news texts tend to have higher MDD values and occur more frequently compared to fiction texts. These constructions allow news writers to convey dense informational content, resulting in longer syntactic dependencies.

While the analysis demonstrates clear genre effects, it should also be noted that sentence length remains the dominant factor affecting dependency distance, as shown by the linear model results. This finding is consistent with previous studies (Ferrer-I-Cancho & Liu, 2014; Jiang & Liu, 2015), which have reported the significant relationship between sentence length and dependency distance. The genre and language effects operate as modulating factors on this main relationship—altering the rate of MDD increase as sentences grow longer rather than overriding the basic length-distance correlation.

These findings contribute to our understanding of how dependency distance minimization principles (Liu, 2008; Futrell et al., 2015; Liu et al., 2017) operate under different genre contexts and typological constraints. While minimizing dependency distance may reduce cognitive processing load (Gibson, 1998; Hawkins, 2004), the results suggest that this principle is not applied uniformly across genres or languages. Instead, it is adapted in ways that reflect the communicative goals and syntactic norms of each genre-language combination.

4 Conclusion

Overall, the current research shows that metrics such as dependency distance can capture genre-sensitive patterns of syntactic complexity, but their interpretation is better understood in the context of both cross-linguistic variation and genre-specific conventions. These insights may shed a new light on genre analysis and highlight the value of quantitative syntax in uncovering structural differences across languages. Future work could broaden this investigation by combining a wider range of genres and additional typologically diverse languages to further assess the cross-linguistic and cross-genre consistency of these findings.

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Appendix A MDDs in different sentence length range across genres in English and Chinese

English	SL range	Sentence Count	MDD
All genres	1-5	936	1.412
All genres	6-10	1574	1.818
All genres	11-15	1288	2.152
All genres	16-20	952	2.393
All genres	21-25	777	2.581
All genres	26-30	558	2.736
All genres	31-35	397	2.906
All genres	36-40	278	3.064
A	1-5	12	1.486
A	6-10	74	1.728
A	11-15	123	2.091
A	16-20	163	2.257
A	21-25	163	2.531
A	26-30	120	2.706
A	31-35	92	2.798
A	36-40	74	2.9
B	1-5	70	1.475
B	6-10	138	1.837
B	11-15	186	2.16
B	16-20	151	2.381
B	21-25	129	2.472
B	26-30	113	2.634
B	31-35	83	2.848
B	36-40	51	2.866
C	1-5	29	1.449
C	6-10	68	1.8
C	11-15	102	2.151
C	16-20	106	2.442
C	21-25	129	2.642
C	26-30	98	2.725
C	31-35	91	2.893
C	36-40	62	3.039
K	1-5	324	1.404
K	6-10	534	1.801
K	11-15	303	2.14

K	16-20	164	2.387
K	21-25	121	2.612
K	26-30	63	2.672
K	31-35	43	3.016
K	36-40	26	3.281
L	1-5	336	1.395
L	6-10	456	1.825
L	11-15	355	2.169
L	16-20	216	2.446
L	21-25	127	2.619
L	26-30	74	2.924
L	31-35	47	3.099
L	36-40	34	3.354
R	1-5	165	1.419
R	6-10	304	1.857
R	11-15	219	2.171
R	16-20	152	2.457
R	21-25	108	2.637
R	26-30	90	2.811
R	31-35	41	2.963
R	36-40	31	3.348
Chinese	SL range	Sentence count	MDD
All genres	1-5	375	1.507
All genres	6-10	826	2.105
All genres	11-15	1000	2.519
All genres	16-20	882	2.847
All genres	21-25	756	3.15
All genres	26-30	510	3.403
All genres	31-35	311	3.613
All genres	36-40	232	3.87
A	1-5	35	1.551
A	6-10	125	2.061
A	11-15	169	2.567
A	16-20	164	2.811
A	21-25	119	3.084
A	26-30	98	3.306
A	31-35	50	3.507
A	36-40	48	3.725
B	1-5	10	1.568
B	6-10	81	2.214
B	11-15	129	2.669
B	16-20	151	2.969
B	21-25	145	3.234
B	26-30	85	3.423
B	31-35	55	3.518
B	36-40	40	4.053
C	1-5	10	1.719
C	6-10	61	2.125
C	11-15	98	2.653
C	16-20	104	3.047
C	21-25	93	3.453
C	26-30	107	3.667
C	31-35	60	3.927
C	36-40	59	4.1
K	1-5	116	1.473
K	6-10	183	2.094
K	11-15	212	2.449
K	16-20	170	2.822
K	21-25	136	3.146
K	26-30	74	3.286
K	31-35	59	3.52
K	36-40	31	3.722
L	1-5	90	1.454
L	6-10	164	2.108
L	11-15	156	2.461
L	16-20	124	2.712
L	21-25	137	3.089
L	26-30	74	3.403
L	31-35	52	3.692
L	36-40	38	3.781
R	1-5	114	1.543
R	6-10	212	2.084
R	11-15	236	2.433
R	16-20	169	2.764
R	21-25	126	2.946
R	26-30	72	3.225
R	31-35	35	3.409
R	36-40	16	3.461