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The influence of linguistic features on L2 Chinese writing quality among students with various L1 backgrounds

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Abstract: Recent studies with automatic text analyzers have explored linguistic measures for predicting writing quality, mostly in English texts by diverse learners. However, research on L2 writing in non-alphabetic languages among students with varied L1 backgrounds remains scarce. This study examines how lexical and syntactic complexity affect writing quality in Chinese-as-a-Second-Language (CSL) students in Hong Kong, using 340 samples from 115 secondary school students with diverse L1 backgrounds. Linear mixed-effects analysis reveals that linguistic indices, including lexical richness and syntactic complexity serve as strong predictors of writing quality, with the combination of logarithmic Type-Token Ratio (LTTR) and syntactic measures (i.e., noun phrase frequency, tree depth, and coordinate phrase usage) explaining 68.5% of the variance. Error analysis demonstrates that L1 word order significantly influences both linguistic complexity patterns and error distributions, with SVO-L1 students demonstrating superior performance compared to other groups. This study extends understanding of linguistic complexity and writing quality relationships to non-alphabetic L2 languages while highlighting the

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mediating role of L1 typological features in shaping measurable aspects of CSL writing development. Theoretical and pedagogical implications are discussed.

Keywords: second language writing; Chinese as a second language; linguistic measure; lexical complexity; syntactic complexity; L1 background

1 Introduction

Writing quality is indicative of a writer's language proficiency, characterized by organization, clarity, consistency, and accuracy. Research has explored the linguistic attributes of first-language (L1) and second-language (L2) writing, focusing on aspects like word choice, sentence structure, coherence, and rhetorical pattern either qualitatively or manually coded (Beers and Nagy 2009; Bulté and Housen 2014; Crossley 2020). In recent decades, advancements in Natural Language Processing (NLP) techniques have led to the availability of automatic tools for text analysis. These tools, such as Coh Metrix (McNamara 2013) and Constructed Response Analysis Tool (Crossley et al. 2016), enable the measurement of objective linguistic features in vast quantities of written texts, which can be used to distinguish between different levels of writing quality (Crossley 2020; McNamara et al. 2010). With these tools, linguistic features that are related to writing quality have been measured, such as lexical complexity and syntactic complexity (Crossley 2020; Hyland 2019; Yoon 2017). While recognizing that writing quality encompasses the multidimensional aspects of organization, clarity, consistency, and accuracy, lexical and syntactic complexity measures serve as observable linguistic indicators that can reflect aspects of these quality dimensions. For instance, appropriate lexical sophistication may enhance precision and accuracy (Ha 2019; Kim et al. 2018; Kyle and Crossley 2016; Lu 2012; Lu and Hu 2022), while varied syntactic structures can contribute to textual organization and coherence (Kim and Ro 2024; Li et al. 2022; Maamuujav et al. 2021). This may be particularly important when evaluating L2 learners' writing, since limitations in lexical and syntactic resources tend to exert a stronger influence on their ability to achieve organization, clarity, consistency, and accuracy than is typically the case for native speakers (Güvendir and Uzun 2023; Vasylets and Marín 2021; Zalbidea 2024). Existing studies have found that indices like lexical sophistication, syntactic complexity, and cohesion effectively predict writing quality, with a focus on English and other Indo-European languages (e.g., Crossley 2020; Crossley et al. 2016; Zhang 2022; Zhang and Lu 2022). In other words, although linguistic complexity measures are not equivalent to writing quality, they have been theoretically and empirically acknowledged as valid proxies for capturing important facets of writing quality. Building on this understanding, linguistic measures can serve as a basis for objective assessments of learners' strengths and weaknesses, especially for L2 writers, and in turn support the design of tailored instruction.

However, the quantitative analysis of objective linguistic features remains underexplored in Chinese, a logographic and non-inflectional language. Moreover, research addressing the influence of students' L1 backgrounds on the linguistic characteristics and quality of their L2 writing remains scarce. Although existing studies have identified the potential crosslinguistic influences on L2 learning, including the transfer of L1 lexical knowledge, rhetorical skill, writing strategy, and writing experience (Forbes and Fisher 2020; Guo and Huang 2020; Wei 2020), there is still a lack of empirical research that systematically examines the influence of L1 backgrounds on L2 writing quality, particularly with the objective measure of linguistic features.

To fill these gaps, this study investigates the predictive value of linguistic features for Chinese-as-a-Second-Language (CSL) writing quality among students with diverse L1 backgrounds. Specifically, this study examines the extent to which lexical and syntactic complexity measures can serve as reliable indicators for predicting overall writing quality. It also explores the potential influence of L1 word order on the relationship between these linguistic features and writing quality. Theoretically, the findings extend the existing research on the association between linguistic features and L2 writing quality to CSL writing development. Practically, this study provides pedagogical suggestions for this specific context.

2 Literature review

2.1 Writing quality and linguistic features

While lexical and syntactic complexity serve as established predictors of writing quality (Crossley 2020), existing research reveals substantial variation across genres and proficiency levels that necessitates more systematic investigation.

For genre-specific patterns, academic writing contexts demonstrate relatively consistent patterns where lexical sophistication serves as a reliable predictor. Kyle and Crossley (2016) established that lexical sophistication consistently predicted independent writing quality among college-level EFL learners, while Crossley and McNamara (2014) identified syntactic indices including clause incidence, noun phrase modification, and verb phrase complexity as powerful predictors in academic essay writing. However, Casal and Lee (2019) found contrasting results in first-year academic writing, where complex nominal structures proved more significant than clausal subordination and coordination. On the other hand, narrative writing contexts reveal more complex relationships between linguistic features and quality assessment. Yoon (2018) demonstrated that combined lexical sophistication measures outperformed individual indices in both narrative and argumentative EFL writing, suggesting genre-specific demands for lexical complexity. In CSL narrative writing, Xu et al. (2024) found that multiple linguistic indices – including lexical diversity, high-difficulty vocabulary, and complex noun phrase ratios – collectively predicted quality among Japanese-speaking students. Ji and Hohenstein (2014) further revealed that narrative motion descriptions exhibited clear L1 transfer patterns, with English-speaking learners following L1 foregrounding strategies. In short, academic writing appears to favor individual complexity measures despite some contradictory findings, while narrative writing consistently requires combined or multiple indices for effective quality prediction, suggesting that genre-dependent cognitive demands fundamentally alter how linguistic complexity contributes to writing assessment.

For learners from different proficiency levels, research has revealed that advanced learners consistently demonstrate strong correlations between complexity measures and writing quality across genres. Zhang (2022) established robust relationships between lexical sophistication and quality in advanced CSL writing, while Lu and Wu (2022) found that noun phrase complexity measures effectively explained variance in advanced learners' syntactic development. Advanced CSL learners typically exhibit sophisticated use of relative clauses, complement structures, and complex modifications that increase structural depth (Lu and Wu 2022). However, intermediate learners present more variable patterns that challenge linear developmental models. Zhang (2021) observed inconsistent lexical variation patterns among Cambodian CSL students, where lexical sophistication and error rates proved more predictive than lexical variation itself. Yu (2021) found that basic T-unit measures – mean length of terminable TC-units and single TC-units per terminable TC-unit – proved more effective predictors than complex syntactic indices for intermediate learners. Overall, it seems that the relationship between linguistic complexity and writing quality is non-linear and proficiency-dependent, with intermediate learners demonstrating inconsistent patterns that challenge traditional assumptions about complexity as a straightforward indicator of writing development. Collectively, these findings underscore the genre-specific and proficiency-specific nature of the relationships between linguistic complexity and writing quality, thereby providing a foundation for the current study to explore the predictability of linguistic indices in CSL writing by learners from different language backgrounds. The predominant focus of the previous research on English texts, with limited exploration of typologically distinct languages, has created significant gaps in understanding how linguistic complexity operates across diverse language systems (Kuiken and Vedder 2019).

2.2 Linguistic features and measurable indices

Chinese presents unique challenges for L2 learners due to its logographic writing system and typological distinctiveness from Indo-European languages (Chang et al. 2014; Leong et al. 2019; Ma et al. 2017; Zhang and Roberts 2019). However, existing CSL writing research has predominantly examined single L1 groups, limiting generalizability and obscuring potential cross-linguistic transfer effects.

At the lexical level, studies have revealed that linguistic features such as average word length, corrected Type-Token Ratio (CTTR) for character richness, and other variations (i.e., log TTR or LTTR, root TTR or RTTR, and Uber TTR or UTTR) are reliable predictors. Average word length serves as a fundamental indicator of lexical sophistication in L2 writing (Crossley 2020). Longer words typically indicate greater morphological complexity and advanced vocabulary usage, as they often contain multiple morphemes, prefixes, or suffixes that demonstrate learners' understanding of word formation processes (Nagy and Anderson 1984). In CSL contexts, average word length becomes particularly significant due to Chinese characters' logographic nature, where each character can represent a complete morpheme or semantic unit (Li and Thompson 1981). Research has shown that advanced CSL learners tend to use longer, more complex words that demonstrate their ability to combine characters effectively (Hao et al. 2023). For instance, beginning learners might use simple two-character words like "好看" (good-looking), while advanced learners might employ more sophisticated expressions like "美轮美奂" (splendid and magnificent), reflecting their expanded lexical repertoire and morphological awareness. Moreover, lexical diversity, measured through various TTR calculations, represents one of the most robust predictors of L2 writing proficiency (Jarvis 2013; McCarthy and Jarvis 2010). CTTR, LTTR, RTTR, and UTTR each capture different aspects of lexical variation while accounting for text length effects that can skew traditional TTR measures (Covington and McFall 2010). CTTR specifically addresses the challenge of text length dependency by applying a correction formula that enables fair comparison across texts of varying lengths (Carroll 1964). In CSL writing, this measure becomes crucial because character-level diversity differs significantly from word-level diversity due to the prevalence of multi-character compound words (Packard 2000). LTTR and RTTR provide additional perspectives on lexical richness by applying mathematical transformations that reduce the impact of text length while preserving sensitivity to vocabulary range (Malvern and Richards 2002). UTTR offers a more sophisticated approach by calculating the ratio of types to the logarithm of tokens squared, making it particularly effective for detecting subtle differences in advanced learners' lexical sophistication (Jarvis 2013). Research in CSL contexts has demonstrated that these TTR variations collectively provide a comprehensive picture of learners' lexical development, with each measure contributing unique insights into different aspects of vocabulary usage patterns (Zhang 2021).

For syntactic indices, studies have shown that features such as sentence length, syntactic tree depth, the quantity and length of noun phrase (NP), the number of coordinate phrase (CP), coordinate phrase per sentence, conjunction word density, functional word density, and sentence-final particle density are reliable predictors. Specifically, sentence length and its standard deviation serve as primary indicators of syntactic complexity and structural variability (Lu 2010; Ortega 2003). In Chinese, where sentence boundaries can be flexible and coordination is often preferred over subordination, these measures capture important aspects of syntactic complexity (Li and Thompson 1981). Furthermore, research has shown that advanced CSL learners demonstrate not only longer average sentences but also greater variability in sentence length, indicating sophisticated control over diverse syntactic structures (Yu 2021). The character-based measurement is particularly appropriate for Chinese, as it accounts for the fact that Chinese sentences can achieve complexity through character combinations rather than morphological inflections. Additionally, the syntactic tree depth feature provides a crucial measure of hierarchical syntactic complexity by capturing the depth of syntactic embedding and structural layering (Lu 2010). In CSL contexts, syntactic tree depth becomes particularly important because Chinese syntax allows for complex structural relationships that may not be immediately apparent from surface-level analysis (Huang 1982). Advanced CSL learners typically demonstrate greater structural depth through sophisticated use of relative clauses, complement structures, and complex modifications that increase parse tree depth (Lu and Wu 2022). This measure effectively distinguishes between learners who rely primarily on coordination (resulting in shallow parse trees) and those who employ subordination and embedding (creating deeper hierarchical structures). NP complexity, measured through the number of noun phrases and the mean length of noun phrases, represents a critical aspect of syntactic sophistication (Biber et al. 2011). These measures capture learners' ability to pack information efficiently through complex nominal structures, which is particularly important in academic and formal writing contexts (Halliday 1994). In CSL writing, NP complexity reflects learners' mastery of Chinese modification patterns, including the use of relative clauses, attributive phrases, and complex nominal compounds (Li and Thompson 1981). Research has demonstrated that NP complexity measures are among the most effective predictors of CSL writing quality, as they reflect both lexical sophistication and structural awareness (Hao et al. 2024a). CP measures capture learners' ability to create balanced syntactic structures and establish logical relationships between ideas (Halliday and Hasan 1976). While coordination might seem simpler than subordination, effective coordinate structure usage requires a sophisticated understanding of semantic relationships and discourse coherence (Martin 1992).

Conjunction word density provides insight into learners' explicit marking of logical relationships between clauses and sentences (Liu 2010). In Chinese, where connectives can be overt or covert, this measure reveals learners' tendency to explicitly mark relationships versus relying on implicit connections (Huang 1982). Research suggests that intermediate learners often overuse explicit conjunctions, while advanced learners achieve a better balance between explicit and implicit connectivity (Liao 2020). Functional word density and sentence-final particle density capture learners' control over grammatical and pragmatic elements that contribute to text coherence and register appropriateness (Li and Thompson 1981). Functional words include prepositions, auxiliary verbs, and other grammatical morphemes that are essential for syntactic structure but often pose challenges for L2 learners (Jiang 2007). Sentence-final particles in Chinese serve crucial pragmatic functions, indicating speaker attitude, emphasis, and discourse relationships (Li and Thompson 1981). Sentence-final particle density thus reflects learners' pragmatic competence and their ability to use these particles appropriately to achieve communicative goals (Yuan and Lin 2019). Advanced CSL learners demonstrate more native-like usage patterns in their deployment of both functional words and sentence-final particles (Hao et al. 2024a). These findings align with theories of syntactic development in L2 writing, which propose that complexity emerges through progressive embedding and modification structures (Ortega 2003).

These features are particularly susceptible to cross-linguistic transfer effects, as they represent areas where L1 and L2 systems may differ significantly (Jarvis 2002). Lexical features such as TTR variations and average word length are influenced by learners' L1 morphological systems and vocabulary organization patterns (Jiang 2000). For instance, learners from alphabetic languages may initially transfer their L1 word formation strategies when constructing Chinese compound words, affecting average word length measurements. Syntactic features show even stronger transfer effects, particularly in areas such as sentence length patterns, coordination preferences, and functional word usage (Odlin 2003). Learners from languages with rigid word order may struggle with the syntactic flexibility of Chinese, leading to distinctive patterns in sentence length (Ji and Hohenstein 2014). Similarly, learners from languages with extensive morphological marking may overuse functional words to compensate for the limited morphological system of Chinese (Yuan 1999). Understanding these transfer effects is crucial as they help explain why certain linguistic patterns emerge in learners' writing and how these patterns relate to overall writing quality (Lu and Ai 2015). The combination of these features provides a comprehensive framework for assessing CSL writing development while accounting for L1-influenced variation patterns.

However, a critical gap exists between broad theoretical claims about L1 transfer and specific empirical investigations. While previous studies have documented transfer effects in lexical representation and syntactic structure (Dodigovic et al. 2017; Paquot 2013), they have not systematically examined how specific L1 typological features, particularly word order, influence measurable linguistic complexity in L2 writing.

2.3 Word order and cross-linguistic transfer

Cross-linguistic transfer in L2 writing operates at multiple levels, yet word order represents a particularly crucial factor due to its fundamental role in syntactic organization and cognitive processing (Hartsuiker and Westenberg 2000; Hawkins 1983). Empirical evidence supports word order as a significant predictor of L2 writing quality through several mechanisms.

First, psycholinguistic research demonstrates that L1 word order patterns create processing preferences that persist in L2 production (MacWhinney 2008). Part of the linguistic distance between L1 and L2 may be captured by their syntactic differences such as word order which not only stands as a significant typological variation across languages but also acts as a powerful influence on language production (Hartsuiker and Westenberg 2000; Hawkins 1983). From the perspective of cross-linguistic research, learners from SOV languages (e.g., Japanese, Hindi) exhibit different syntactic packaging strategies compared to SVO learners (e.g., English, Arabic) when writing in Chinese (Ji and Hohenstein 2014). In addition, corpus studies reveal that word order differences correlate with specific error patterns and complexity measures in L2 writing (Jarvis 2002; Lu and Ai 2015). Furthermore, error analysis serves as a critical complementary approach to complexity measurement, as error types provide direct evidence of L1 interference and developmental stages in L2 acquisition (Corder 1975, 1981; James 1998). Systematic error patterns reflect underlying interlanguage development and reveal how L1 structural preferences manifest as systematic deviations from the target language norms (Selinker 1972). Moreover, the distribution and frequency of specific error types correlate with writing quality assessments, with morphosyntactic errors showing stronger negative correlations with holistic scores than lexical or discourse-level errors (Bitchener and Knoch 2010a, 2010b; Ferris et al. 2006). For CSL learning specifically, Zhang and Gnevsheva (2022) revealed that Japanese learners outperformed Arabic and English students in the use of classifiers in L2 Chinese. Also, when certain linguistic structure varies significantly in L1 and L2, this feature tends to be acquired late until learners achieve an advanced level (Ji and Hohenstein 2014; Yuan 1999). Usage-Based Theory (Tomasello 2003) also indicates that syntactic complexity emerges from learners' ability to manipulate word order patterns, making word order analysis a valid proxy for examining broader L1 influences on writing quality. In sum, word order and error patterns together reflect fundamental dimensions of cross-linguistic transfer and serve as productive lenses for investigating how L1 backgrounds shape measurable aspects of CSL writing quality.

Although the above studies demonstrate that word order and error types are suitable dimensions for examining cross-linguistic transfer in relation to learners' L1 backgrounds – serving as both observable manifestations of transfer and quantifiable indicators of its impact on L2 writing – important limitations still exist: (1) most cross-linguistic studies have examined broadly defined transfer effects without isolating specific typological features; (2) previous CSL research has not systematically compared learners from different word order backgrounds; and (3) the relationship between L1 word order and measurable linguistic complexity in CSL writing remains unexplored.

2.4 Research questions

Hong Kong's biliteracy and trilingualism policy (i.e., Chinese and English for writing, and Cantonese, Mandarin, and English for speaking) underscores the critical importance of mastering both spoken Cantonese and written Chinese. As a result, proficiency in Chinese is essential for success within the local education system, presenting significant challenges for the city's immigrant population, which constitutes approximately 10% of the total population (Loh et al. 2018). The differences between spoken Cantonese and standard written Chinese further complicate matters for these L2 Chinese learners, particularly in reading and writing (Zhu et al. 2024). However, research on teaching Chinese to students from various L1 backgrounds is still limited. Moreover, the interconnected nature of how L1 typological features influence multiple dimensions of L2 writing performance remains underexplored, particularly regarding the mediating mechanisms through which word order differences and error patterns collectively shape lexical and syntactic complexity development.

For these reasons, this study adopts an integrated analytical approach to examine the multifaceted relationships between L1 backgrounds and CSL writing performance, aiming to answer the following three research questions:

(1) At the lexical level and the syntactic level, what linguistic features can be used to predict the quality of CSL writing?
(2) How do different word orders as a crucial syntactic feature in students' L1 backgrounds influence lexical and syntactic complexities in their CSL writing, and through what mechanisms do these influences manifest in writing errors and overall writing quality?

(3) In what ways are word order differences and the associated writing error patterns linked to the relationship between learners' L1 backgrounds and different levels of CSL writing quality?

3 Materials and methods

3.1 Participants

In total, 345 (5 absent) integrated writing samples were collected, representing three writing submissions from 115 students (59 females, 56 males, $\text{Mean}_{\text{age}} = 16.63$) who had been learning CSL in Hong Kong high schools. These participants were selected through convenience sampling, as they all attended three-hour Chinese language classes once a week as part of the Applied Learning Chinese for non-native student subject (ApL(C) subject). The ApL(C) subject is a government-recognized elective designed for CSL students with less than six years of school-based Chinese education or those who followed a simplified curriculum not designed for native speakers. It serves as an alternative to the mainstream Chinese subject, focusing on practical language use and social integration rather than advanced literary content. The subject covers reading, writing, and speaking, with writing instruction primarily assessed through integrated writing (IW) tasks, a format that students are highly familiar with. The medium of instruction for this course is Cantonese.

On average, students had been studying Chinese for 11.4 years. The course admits CSL students with less than six years of school-based Chinese education or those who followed a simplified curriculum not designed for native speakers, indicating intermediate or lower proficiency in Chinese reading and writing.

In a background survey, students reported their L1 or dominant languages. To better examine the crosslinguistic transfer effect, students' L1s were categorized according to the word order. Specifically, L1s were grouped as SOV languages (e.g., Urdu, $N = 93$), SVO languages (e.g., English, $N = 13$), and VSO languages (e.g., Tagalog, $N = 9$).

3.2 Instruments

Students were asked to complete three Chinese IW tasks in which they needed to combine reading, interpreting graphical information, and writing skills. These tasks involved diverse input materials, such as short texts, infographics, tables, and dialogues, along with task-specific prompts that guided students to synthesize information and express their opinions or arguments (Zhu 2015; Zhu et al. 2016). These tasks are also used in school-based assessments in secondary schools and the Hong Kong Diploma of Secondary Education (HKDSE) for Chinese proficiency evaluation. While these practical writing tasks impose certain genre-specific constraints on lexical and syntactic choices, they reflect authentic writing demands that CSL students encounter in academic and professional contexts, thereby ensuring ecological validity and real-world applicability of our findings.

The topics were related to local life and work: the first task was an after-visit report of the facilities and services provided in a hotel, the second task was a complaint letter to address the issues that occurred during a delivery service, and the third task was a cover letter for a job application. In each task, students were instructed to read the writing prompt (300–500 characters) and write an essay of at least 250 characters within a ninety-minute time limit. The grading rubrics evaluated students' writing performance in three subsections, namely content integration (20 points), language expression (10 points), and overall structure (10 points). Each component was assessed using a five-level rating scale (i.e., level 1 beginning, level 2 developing, level 3 average, level 4 good, and level 5 proficient). For content, level 1 corresponded to 0–4 points and level 5 corresponded to 17–20 points. For language expression and structure, level 1 ranged 0–2 points, while level 5 ranged 9–10 points. An experienced Chinese language teacher and a PhD-level researcher specializing in Chinese language education served as raters for the writing assessments. Before scoring, the raters received training on the rubric and then assigned scores to the student essays independently. The inter-rater reliability, measured using Spearman's correlation, was 0.773, indicating an acceptable level of agreement. Any scoring discrepancies were resolved through discussion and consensus.

3.3 Data collection

The three IW tasks were administered over three semesters, each eight months apart. The 85-hour writing course ran for one and a half years, with weekly 2–3 hour sessions. The ApL(C) subject was structured into three proficiency levels, with one level covered each semester and progressive instruction in reading, writing, and speaking. Teachers handed out the test papers to students and provided any necessary assistance during the tests, such as explaining task instructions or providing additional blank papers, without offering linguistic or content-related help. This ensured that students completed the tasks independently under exam-like conditions. After the test, all test papers were scanned and transcribed verbatim. The study received ethical approval from the Departmental Research Committee, and all participants signed informed consent forms.

3.4 Data analysis

3.4.1 Measures of linguistic features

Currently, tools that are publicly available for automatic Chinese text analysis include Chi-editor (Jin and Lu 2018), Chinese Coh-Metrix, CRIE (Sung et al. 2016), and the Common Text Analysis Platform (CTAP, Cui et al. 2022). Among these tools, CTAP has been used to measure the linguistic features as it covers the most text indexes for Chinese at both lexical and syntactic levels (Chen and Meurers 2016). Specifically, CTAP employed the Stanford CoreNLP toolkit to preprocess the selected writing samples through sentence splitting, tokenization, part-of-speech tagging, constituency parsing, and dependency parsing, creating the annotated linguistic foundation for feature extraction. Based on findings reviewed in the literature, the following 15 were selected: in the lexical level, average word length (AWL), CTTR, LTTR, RTTR, and UTTR were measured; while in the syntactic level, measured complexity indices include sentence length by character (Sen_Leng), sentence length standard deviation (Sen_Leng_SD), mean parse tree depth feature (TDF), number of noun phrase (NP_Num), mean length of noun phrase (NP_Leng), number of coordinate phrase (CP_Num), coordinate phrase per sentence (CP/Sen), conjunction word density (Density_Conj), functional word density (Density_Fun), and sentence-final particle density (Density_Par) (see more in Appendix A). The CTAP platform then automatically calculated the 15 selected features across both lexical and syntactic levels. The automated processing of CTAP ensured consistent measurement across all texts, with results exported as numerical values for subsequent statistical analysis. The platform's comprehensive set of Chinese linguistic complexity measures and its open-source architecture made it particularly suitable for this cross-linguistic transfer study, providing reliable and theoretically grounded linguistic complexity assessment.

3.4.2 Statistical analysis

For statistical analyses, Pearson correlations were calculated for all selected linguistic features as the first step. Then three linear mixed-effects models were conducted using the lmer() function with the lme4 package in R (Bates et al. 2015; Cunnings 2012; Linck and Cunnings 2015). As the writing samples are repeated measures, mixed-effects models serve as an appropriate approach to control individual variation and handle unbalanced data (e.g., unequal group sizes across L1 groups). The sequential modeling approach follows the principle of hierarchical model building recommended for complex linguistic data (Winter 2020). This approach is theoretically motivated by usage-based theories of language acquisition, which suggest that L2 learners' linguistic features develop through the interaction of frequency effects, cognitive processing mechanisms, and cross-linguistic influence (Ellis 2017). To address research question 1, we conducted two models. To identify the significant linguistic measures among the selected features, model 1 examined all the linguistic indices without any interaction. To test the potential interactions between any identified linguistic indices from model 1, model 2 involved interactions between each linguistic measure in the formula.To address research question 2, model 3 examined the effect of L1 word order based on the results of model 1 and model 2. The theoretical justification for using linear mixed-effects models stems from their alignment with usage-based theories of language learning, which recognize both individual variation in learning trajectories (captured through random intercepts) and systematic group-level patterns influenced by L1 typological features (captured through fixed effects). All models included individual variation as a random intercept. Finally, a likelihood ratio test was conducted using anova() for model comparison, following established practices for nested model evaluation in linguistic research (Baayen et al. 2008).

3.4.3 Error analysis

In SLA research, error analysis collects, classifies, and analyzes errors in the written and spoken performance of foreign language learners (Corder 1975; Ellis and Barkhuizen 2005; Heydari and Bagheri 2012; James 2013; Richards 1980). It plays a crucial role in language teaching and learning for its ability to account for linguistic competence, identify learning processes and strategies, and provide reference to language pedagogy (Bitchener and Knoch 2010a, 2010b; Hinkel 2002; Richards 1980). Here, errors are defined as deviations from the norms of the target language that affect communication clarity and accuracy (James 2013). Nine writing samples were randomly selected from each L1 group and each tier of grades (top 15%, middle 70%, and bottom 15%). All errors in the writing samples were identified and categorized into lexical and syntactic errors. Each error was described and explained for their possible sources.

4 Results

4.1 Significant linguistic measures

Based on the correlation analysis results in Table 1, several linguistic features demonstrate significant associations with overall writing quality. The strongest

Table 1: Pearson correlations between linguistic features and writing quality.

Linguistic feature	*r*	*t*	*df*	*p*	95 % CI
NP_Num	0.620**	14.522	338	<0.001	[0.550, 0.681]
TTR	0.653**	15.838	338	<0.001	[0.587, 0.710]
RTTR	0.653**	15.838	338	<0.001	[0.587, 0.710]
LTTR	−0.431**	−8.783	338	<0.001	[−0.514, −0.340]
NP_Leng	−0.333**	−6.490	338	<0.001	[−0.424, −0.235]
AWL	−0.324**	−6.296	338	<0.001	[−0.416, −0.225]
CP_Num	0.306**	5.910	338	<0.001	[0.206, 0.399]
Density_Fun	0.182**	3.405	338	<0.001	[0.077, 0.283]
TDF	0.138*	2.552	338	0.011	[0.032, 0.240]
Sen_Length_SD	0.130*	2.404	338	0.017	[0.024, 0.233]
CP/Sen	−0.101	−1.876	338	0.062	[−0.206, 0.005]
Density_Conj	−0.096	−1.767	338	0.078	[−0.200, 0.011]
UTTR	−0.046	−0.845	338	0.398	[−0.152, 0.061]
Density_Par	0.033	0.609	338	0.543	[−0.074, 0.139]
Sen_Leng	−0.006	−0.116	338	0.908	[−0.113, 0.100]

Individual = 115, observation = 340. *** $p < .001$, ** $p < .01$, * $p < .05$.

positive correlations were observed for lexical diversity measures, with both TTR and RTTR showing identical strong correlations ($r = 0.653$, $p < 0.001$), followed by NP frequency (NP_Num, $r = 0.620$, $p < 0.001$), suggesting that higher-quality writing is characterized by greater lexical variety and more frequent use of NPs. Conversely, several features showed significant negative correlations with writing quality, including LTTR ($r = -0.431$, $p < 0.001$), NP_Leng ($r = -0.333$, $p < 0.001$), and AWL ($r = -0.324$, $p < 0.001$), indicating that better writing tends to feature more concise linguistic structures. Additional significant positive predictors included CP_Num ($r = 0.306$, $p < 0.001$) and Density_Fun ($r = 0.182$, $p < 0.001$), while several features showed weak or non-significant associations with writing quality. These correlation patterns allow us to examine the relative contributions of these linguistic dimensions while accounting for individual-level variation across the participants and writing tasks in our hierarchically structured dataset in the following linear mixed-effects regression models.

To address research question 1, Tables 2 and 3 list the results of how the selected linguistic indexes can predict students' writing quality according to the holistic scores. Model 1 shows that among the 15 linguistic features, one lexical index (i.e., LTTR) and five syntactic indices (i.e., NP_Num, TDF, NP_Leng, Density_Conj, and CP/Sen) reached significance. As mentioned, model 2 considers the potential interactions among all significant linguistic indexes. Results in Table 3 show that (1) CP/Sen plays a key role both by itself and by interacting with other linguistic parameters;

Table 2: Model 1: linear mixed-effects model of linguistic indexes without interaction.

	Estimate	Std. error	*t* value	Pr(>|t|)
(Intercept)	5.596e+01	1.655e+01	3.382	0.000828***
NP_Num	7.713e−02	1.493e−02	5.165	0.61e−07***
TDF	1.149e+00	3.897e−01	2.949	0.003467**
NP_Leng	−1.427e+00	5.861e−01	−2.435	0.015532*
Density_Conj	9.605e+01	4.874e+01	1.970	0.049850*
CP/Sen	−4.964e+00	2.421e+00	−2.051	0.041236*
Log TTR	−4.111e+01	1.786e+01	−2.302	0.022131*

Individual = 115, observation = 340, marginal R^2 = 0.360, conditional R^2 = 0.583, intercept variance = 12.94 (SD = 3.60), residual variance = 24.12 (SD = 4.91). *** $p < .001$, ** $p < .01$, * $p < .05$.

Table 3: Model 2: linear mixed-effects model of linguistic indexes with interaction.

	Estimate	Std. error	*t* value	Pr(>|t|)
(Intercept)	−695.8864	1,000.7864	− 0.695	0.487481
CP/Sen	7,303.0848	2,119.3811	3.446	0.000664***
TDF × CP/Sen	−694.1998	210.8608	−3.292	0.001133**
NP_Leng × CP/Sen	−997.1792	387.3377	−2.574	0.010587*
CP/Sen × Log TTR	−8,269.1297	2,316.9524	−3.569	0.000427***
TDF × NP_Leng × CP/Sen	91.1516	38.3541	2.377	0.018193*
TDF × CP/Sen × Log TTR	790.5823	231.2425	3.419	0.000731***
NP_Leng × CP/Sen × Log TTR	1,116.5634	410.8491	2.718	0.007014**
TDF × NP_Leng × CP/Sen × Log TTR	−102.8064	40.8579	−2.516	0.012467*

Individual = 115, observation = 340, marginal R^2 = 0.548, conditional R^2 = 0.676, intercept variance = 7.77 (SD = 2.79), residual variance = 19.72 (SD = 4.44). *** $p < .001$, ** $p < .01$, * $p < .05$.

and (2) in general, the lexical index and syntactic indices interactively affect writing quality.

To address research question 2, Table 4 demonstrates the results when the L1 word order effect was considered. It shows that besides the linguistic parameters, L1 word order is a significant predictor. Specifically, students whose L1s are SVO languages performed better than other students in Chinese IW tasks. The linguistic indices, as revealed in model 2, are still significant predictors. Table 5 shows the standardized coefficients of each significant parameter in model 3 at the same significant level. For individual parameters, NP_Num (β = 0.49), followed by L1 word order (β = 0.30), has the strongest impact on writing quality prediction. Among the interactions of parameters, results demonstrate that the interaction between LTTR and NP_Num affects students' writing quality to the greatest extent (β = 0.37).

Table 4: Model 3: linear mixed-effects model of L1 word order effects.

	Estimate	Std. error	*t* value	Pr(>|t|)
(Intercept)	−5.926e+02	9.944e+02	−0.596	0.551776
CP/Sen	7.207e+03	2.105e+03	3.424	0.000715***
L1_SVO	2.456e+00	1.137e+00	2.160	0.033864*
TDF × CP/Sen	−6.843e+02	2.094e+02	−3.268	0.001228**
NP_Leng × CP/Sen	−9.840e+02	3.847e+02	−2.558	0.011071*
CP/Sen × LTTR	−8.142e+03	2.301e+03	−3.538	0.000476***
TDF × NP_Leng × CP/Sen	8.955e+01	3.809e+0	2.351	0.019455*
TDF × CP/Sen × LTTR	7.775e+02	2.297e+02	3.386	0.000819***
NP_Leng × CP/Sen × LTTR	1.098e+03	4.080e+02	2.690	0.007598**
TDF × NP_Leng × CP/Sen × LTTR	−1.006e+02	4.058e+01	−2.479	0.013791*

Individual = 115, observation = 340, marginal R^2 = 0.562, conditional R^2 = 0.685, intercept variance = 7.59 (SD = 2.75), residual variance = 19.46 (SD = 4.41). *** $p < .001$, ** $p < .01$, * $p < .05$.

Table 5: Standardized coefficients of each significant parameter in model 3.

Parameter	Std. coef.	95 % CI
(Intercept)	0.14	[0.03, 0.25]
NP_Num	0.49	[0.40, 0.59]
TDF	0.13	[0.02, 0.24]
L1_SVO	0.30	[0.03, 0.57]
NP_Num × CP/Sen	−0.16	[−0.30, −0.02]
NP_Num × LTTR	0.37	[0.27, 0.47]
NP_Num × TDF × LTTR	−0.18	[−0.34, −0.02]
NP_Num × TDF × CP/Sen × LTTR	−0.22	[−0.35, −0.09]

Based on this, model 2 and model 3 were compared via a likelihood ratio test using anova(). As Table 6 shows, indexes including chi-square value, degree of freedom, and *p*-value indicate that model 3 with L1 considered fits our data better. In other words, character richness, syntactic complexity, and L1 word order are significant predictors of students' CSL writing quality.

4.2 L1 word order and error analysis

For research question 3, the statistical results above reveal that SVO-L1 students performed significantly better than their SOV-L1 and VSO-L1 peers. Table 7

Table 6: Model comparison.

	npar	AIC	BIC	LogLikelihood	Deviance	Chisq	Df	Pr(>Chisq)
Model 2	34	2,101.7	2,231.9	−1,016.8	2,033.7			
Model 3	36	2,098.4	2,236.2	−1,013.2	2,026.4	7.3321	2	0.02558 *

*** $p < .001$, ** $p < .01$, * $p < .05$.

Table 7: Essay example analysis.

#	L1	Score tier	Log TTR	NP_Num	TDF	Density_Conj	CP/Sen	NP_Leng
1	SVO	Top 15 %	0.87	246	11.30	0.03	0.59	4.96
2	SVO	Middle 70 %	0.88	93	9.14	0.04	0.71	5.55
3	SVO	Bottom 15 %	–	–	–	–	–	–
4	SOV	Top 15 %	0.87	153	9.57	0.03	0.61	4.70
5	SOV	Middle 70 %	0.86	65	11.86	0.01	0	3.23
6	SOV	Bottom 15 %	0.91	13	9	0.025	0.5	3.62
7	VSO	Top 15 %	0.87	123	10.2	0.01	0.4	5.2
8	VSO	Middle 70 %	0.88	63	7.25	0.037	0.42	5.03
9	VSO	Bottom 15 %	–	–	–	–	–	–

demonstrates the linguistic complexity indices for each writing sample of students from different L1 groups and score tiers. No SVO or VSO student was below 15% in the score tier. Overall, lexical richness does not differ significantly among the selected samples. For syntactic indexes, the top SVO sample #1 exhibits the highest scores in NP_Num and TDF which are the two single influential linguistic parameters as shown in Table 5. For all top-tier samples, #1 demonstrated the highest scores in most syntactic indexes, followed by #4, then #7. And a similar pattern also occurs in the middle-tier samples. This echoes the L1 effect according to the previous statistical analyses in two ways: first, students from SVO L1 backgrounds generally achieved higher scores in most linguistic indexes than students from other L1 backgrounds; and second, students from SVO L1 backgrounds generally outperformed their peers from other L1 backgrounds in overall writing quality based on both human judgments and the objective linguistic indices. To further explain how their writings differ regarding the L1 effect, error analysis was conducted.

Overall, students had more syntactic errors than lexical errors at all score tiers (see Table 8). Lexical errors can be categorized into two types: formal errors where the grammatical function of the target morpheme is not accurately expressed

Table 8: Error analysis of the essay examples.

#	L1	Score tier	Lexical error	Syntactic error
1	SVO	Top 15 %	4 (100 % formal)	14 (word order 7.14 %; syntactic structure 28.56 %; missing constituent 42.86 %; redundant constituent 21.43 %)
2	SVO	Middle 70 %	8 (formal error 62.5 %; semantic error 37.5 %)	14 (word order 0 %; syntactic structure 50 %; missing constituent 50 %; redundant constituent 0 %)
3	SVO	Bottom 15 %	–	–
4	SOV	Top 15 %	7 (formal error 42.86 %; semantic error 57.14 %)	12 (word order 8.33 %; syntactic structure 16.67 %; missing constituent 41.67 %; redundant constituent 33.33 %)
5	SOV	Middle 70 %	2 (formal error 50 %; semantic error 50 %)	6 (word order 0 %; syntactic structure 16.67 %; missing constituent 16.67 %; redundant constituent 66.67 %)
6	SOV	Bottom 15 %	2 (formal error 50 %; semantic error 50 %)	2 (word order 50 %; syntactic structure 0 %; missing constituent 0 %; redundant constituent 50 %)
7	VSO	Top 15 %	3 (formal error 0 %; semantic error 100 %)	4 (word order 0 %; syntactic structure 50 %; missing constituent 25 %; redundant constituent 25 %)
8	VSO	Middle 70 %	0	13 (word order 30.77 %; syntactic structure 7.69 %; missing constituent 53.85 %; redundant constituent 7.69 %)
9	VSO	Bottom 15 %	–	–

(e.g., the missing aspect marker *-le*), and semantic errors in which the target morpheme is semantically used inappropriately (e.g., '*through this experience*' written as '*pass through this experience*'). At the syntactic level, four types of errors were identified: word order, syntactic structure, missing constituent, and redundant constituent.

5 Discussion

5.1 Linguistic features and CSL writing quality

According to the statistical results, the combination of lexical complexity index (i.e., LTTR) and three syntactic complexity indices (i.e., CP/Sen, NP_Leng, and TDF) appears to be powerful predictors which explains 0.676 variance of the data. At the lexical level, TTR measures lexical richness by calculating the number of different terms and the diversity of the vocabulary in the text (Torruella and Capsada 2013). Basic forms of TTR, such as TTR, RTTR, and CTTR, are text-length sensitive, while LTTR seems to be a more reliable index for Chinese character richness in this case. It suggests that besides previously identified powerful predictors such as lexical variation, lexical frequency, and lexical sophistication (Hao et al. 2023; Zhang 2021), lexical richness also plays a crucial role in distinguishing CSL writing proficiency. On one hand, Chinese characters may be used as independent morphemes or combined to form new words allowing students to improve their lexical richness by not only adopting new vocabulary but also combining the known ones (Hao et al. 2024b; Masini 1993). On the other hand, as a logographic language, Chinese lacks morphological changes as in English, but can demonstrate meaningful information in character writing (Han and Bi 2009; Zhang and Xing 2023). In this case, using a greater variety of different characters allows for the expression of broader and more precise meanings in composition (Loh et al. 2018).

At the syntactic level, indices including TDF, CP/Sen, and NP_Leng proved to be effective predictors. TDF as a skeleton-based syntactic feature is measured based on the height of the parse tree (Cui et al. 2022; Massung et al. 2013). Studies have shown that TDF can effectively reflect syntactic complexity: the higher the parse tree, the more complex the sentence (Cui et al. 2022; Wu and Hu 2021). Consistent findings were identified in CSL data. Chinese has a relatively flexible word order and depends more on discursive structures to convey grammatical relationships. This allows for greater variation in syntactic structures, thereby increasing syntactic complexity (Li and Thompson 1981; Shi 2000). Additionally, CP/Sen measures syntactic complexity regarding phrasal elaboration and may serve as a predictable index (Crossley and McNamara 2014). Features such as serial verb construction and topic-comment structure signal the unique syntactic complexity in Chinese, and CP/Sen reflects the frequency of complex clauses which closely relates to CSL writing quality. Lastly, NP_Leng captures complexity about the head noun and modifiers used to describe the NP. In English, NP complexity has shown to be a reliable predictor (Lan et al. 2019, 2022; Parkinson and Musgrave 2014). While in Chinese which lacks inflectional changes but has head-final NP construction, syntactic complexity could be better captured by NP_Leng that indicates the phrasal internal structure. Consequently, learners who are able to write longer and more complex NPs are often more proficient writers. Models 2 and 3 show that when interactions among tested linguistic indices are not involved, CP/Sen appears to be the only determinant. Results in Table 4 reveal that NP_Num has the strongest predictive power among all the single predictors. Overall, this suggests that on one hand, compared with lexical complexity, syntactic complexity explains more of the variance in CSL writing quality. Moreover, in Chinese, grammatical functions are basically realized through the use of function words which hereby largely determines the complexity of the whole sentence. The combination of lexical and syntactic features constitutes a significant part of the determinants to distinguish CSL students' writing proficiency.

5.2 L1 transfer and word order errors

Considering the crosslinguistic transfer effect, Model 3 examined how students' L1 word order may affect the predictability of the linguistic indices for CSL writing quality. As results demonstrate, students whose L1s were characterized by an SVO word order tended to achieve higher scores than their peers who spoke other types of L1s. Previous studies have shown that word order errors, including the missing obligatory constituent, redundant component in the sentence, and grammatical misconstruction, were more frequently encountered in the acquisition of Chinese syntax than other error types (Chang 1992; Yu and Chen 2012). Since SVO word order is the same in Chinese as the target language, SVO-L1 students may encounter fewer struggles in basic syntactic structure than SOV-L1 or VSO-L1 students. According to the literature, lexical errors, including missing morpheme, redundant morpheme, misuse, and incorrect morphological structure (Lu 1987; Wu 2020; Xing 2012), and syntactic errors such as word reordering, incorrect syntactic structure, missing constituent, and redundant constituent (Ji and Hohenstein 2014; Liao 2020) were identified in students' writing samples. On one hand, as grammatical functions are largely realized on lexical items in Chinese, lexical and syntactic errors often interact with each other and make it more challenging for non-SVO students. Furthermore, compared with inflectional languages, the lack of morphological changes in Chinese may reduce the difficulty of language learning, but it may also lead to errors when students whose L1s are inflectional languages try to express temporal, number, or case changes in their CSL writing. The examples below demonstrate each type of the syntactic errors.

In example 1, the subject 1SG-formal was not introduced until the second clause even though the main verb "*get to know*" required a grammatical subject. Part of this error may be attributed to the student's L1 Tagalog with a VSO word order in which the subject would follow the second predicate "*apply*".

(1) Word order

Student sample

Cóng	“chénguāng rìbào”	guǎnggào	zhōng	dé
從	《晨光日報》	廣告	中	得
From	‘Chenguang Daily’	advertisement	in	get
zhī	zhāopìn	yī	shì	
知	招聘	一	事,	
know	recruitment	one	thing,	
běnrén	yìngzhǐ	fēndiàn	jīnglǐ	zhùlǐ
本人	應徵	分店	經理	助理
1SG-formal	apply	the branch store	manager	assistant
de	zhíwèi			
的	職位。			
NOM	position			

Corrected version

Běnrén	cóng	“chénguāng rìbào”	guǎnggào	zhōng
本人	從	《晨光日報》	廣告	中
1SG-formal	From	‘Chenguang Daily’	advertisement	in
dé	zhī	zhāopìn	yī	shì
得	知	招聘	一	事,
get	know	recruitment	one	thing,
tè	*lái*	yìngzhǐ	fēndiàn	jīnglǐ
特	來	應徵	分店	經理
especially	*come*	apply	the branch store	manager
zhùlǐ	de	zhíwèi		
助理	的	職位。		
assistant	NOM	position		

VSO sample #8: ‘I learned about the recruitment from an advertisement in “Chenguang Daily” and came here to apply for the position of assistant manager at the branch store.’

In example 2, the NP “*the teacher from our school*” presents a head-final structure with the two determiners “*our*” and “*school*” precede the root “*teacher*”. The genitive marker -de marks a possessive relationship between the modifier phrase “our school” and the head noun “*teacher*” (Li 2010; Li and Thompson 1981). However, the student inserted the genitive marker “*-de*” between “*our*” and “*school*”, leaving the “*teacher*” unattached to its determiners. This mistake may be attributed to the grammatical requirements of possessive constructions and agreement in the student’s L1 language Hindi (Kachru 1970; Pareek 2022).

(2) Syntactic structure

Student sample

Wǒmen	de	xuéxiào	lǎoshī
我們	的	學校	老師
1PL	GEN	school	teacher

Corrected version

Wǒmen	xuéxiào	de	lǎoshī
我們	學校	的	老師
1PL	school	GEN	teacher

SOV sample #6: 'The teacher from our school'

Example 3 demonstrates that the student had an incomplete object to expression "*the ability to use languages*" and their L1 Tagalog which has a VSO word order may pay a role in the construction of Chinese syntactic structure. In Tagalog, the subject "*I*" would be placed between the two VPs "*have the ability*" and "*use languages*". The mismatch between the subject "*I*" and the serial verbal phrase "*to use languages*" instead of the main VP "*have the ability*" turned out an error in the student's CSL writing as "*have the languages*" while part of the object "*the ability to*" was absent. And the missing constituent may be dropped during the process from the dismantlement of the L1 expression to the reconstruction of the L2 sentence.

(3) Missing constituent

Student sample

Běnrén	jùyǒu	liúlì	guǎngdōng huà	liánghǎo	yīngwén	jí	pǔtōnghuà
本人	具有	流利	廣東話、	良好	英文	及	普通話
1SG-formal	have	fluent	Cantonese	good	English	and	Mandarin

Corrected version

Běnrén	jùyǒu	*liúlì*	*shǐyòng*	guǎngdōng huà	liánghǎo	yīngwén	jí
本人	具有	流利	使用	廣東話、	良好	英文	及
1SG-formal	have	*fluent*	*use*	Cantonese	good	English	and
de	*nénglì*						
的	能力						
NOM	*ability*						

VSO sample #8: 'I have the ability to speak fluent Cantonese, good English and Mandarin'

Lastly, in example 4, the student had two similar main verbs, namely "*be able to*" and "*know how to*" in the same clause. Here the student formed the correct word order for "*type in Chinese and English*" but used two similar verbs unnecessarily.

When the subject was absent in the sentence, the VO structure could not be appropriately composed, and the main verb was repeated redundantly.

(4) Redundant constituent
Student sample

Nénggòu	*dǒngdé*	zhōng	yīngwén	dǎzì
能夠	懂得	中	英文	打字
Be able to	*know (how to)*	Chinese	English	type

Corrected version

Dǒngdé	zhōng	yīngwén	dǎzì
懂得	中	英文	打字
know (how to)	Chinese	English	type

VSO sample #8: '(I) know how to type in Chinese and English.'

5.3 L1 word order and related error patterns as factors shaping CSL writing quality

In addressing research question 3, our findings indicate that L1 word order differences exert a significant influence on both syntactic complexity and error distributions in CSL writing. Learners with SVO backgrounds, whose L1 structures align with Chinese word order, can devote greater cognitive resources to syntactic elaboration rather than resolving basic sequencing conflicts. This alignment helps explain their superior performance on NP_Num (β = 0.49) and more effective use of coordination. In contrast, learners from SOV and VSO backgrounds face additional processing demands due to incongruent word orders, which constrain the development of comparable levels of syntactic sophistication (Hao et al. 2024a; Ji and Hohenstein 2014; Liao 2020). Error analysis further substantiate these differences. VSO learners demonstrate notably high rates of word order errors (30.77% in mid-tier scripts) and missing constituent errors (53.85%), reflecting the challenges of restructuring verb-initial patterns into subject-initial ones (Hartsuiker and Westenberg 2000; Hawkins 1983; Yu and Chen 2012). By comparison, SOV learners show elevated levels of syntactic structure errors and redundant constituent errors, suggesting difficulties in adapting from head-final to head-initial constructions in Chinese NPs. These distinct error profiles provide observable evidence of how typological constraints channel learners along divergent developmental pathways.

Moreover, model results reveal that L1 word order moderates the relationship between linguistic complexity and writing quality. The significant interaction between LTTR and NP_Num (β = 0.37) suggests that lexical and syntactic development interact differently across L1 groups. For SVO learners, the positive association between these measures reflects synergistic growth, where lexical richness supports syntactic elaboration. Non-SVO learners, however, appear constrained by the additional cognitive load of reconciling word order conflicts, resulting in weaker integration of lexico-syntactic resources. These patterns further imply that the effects of L1 word order extend beyond direct transfer, shaping learners' metalinguistic awareness and strategic competence (Yuan and Lin 2019; Zhang 2018). The stronger performance of SVO learners across multiple indices (TDF, NP_Num, CP/Sen) suggest not only structural facilitation but also enhanced control over the allocating attentional resources to higher-level discourse and rhetorical concerns. Model comparisons lend additional support: incorporating L1 effects significantly improved model fit ($p < 0.05$), accounting for 1.4% additional variance beyond linguistic measures alone. This highlights the explanatory value of typological features as complementary to established predictors of writing development. The findings align with usage-based theories, which posit that L1–L2 structural similarities promote more efficient processing and acquisition of language competencies (Ellis 2017; Kim and Ro 2024; Tomasello 2003).

5.4 Pedagogical implications

First, CSL writing instruction should aim to address CSL students' lexical richness, along with their vocabulary size, literacy skills, word recognition skills, and semantic and pragmatic knowledge. Studies have shown that L2 vocabulary acquisition tends to fossilize during the L1 lemma mediation when the L1 lemma information is transferred into the L2 lexical entry (Jiang 2000). Building on this observation, IW tasks, where learners are provided with reading materials and prompts, may offer opportunities for learners to consolidate and potentially expand their L2 vocabulary. Second, syntactic complexity, especially the complex NP structures, the use of CPs, and complicated sentence structures, needs to be emphasized in class. The inclusion of corresponding examples and practices will facilitate students in adopting various and more advanced syntactic structures in writing. In addition, Liao (2020) found that as students' writing proficiency improves, their lexical accuracy showed a V-shaped trajectory while syntactic accuracy demonstrated a linear development. The mismatch between lexical and syntactic competence needs to be acknowledged and addressed for students at different developmental stages. Third, given the mediating role of L1 word order in CSL writing development, instructors should implement differentiated instructional approaches that address the specific structural challenges faced by different L1 groups. For SOV-L1 students, explicit instruction on Chinese head-initial noun phrase constructions and practice with coordinate structures may be particularly beneficial. For VSO-L1 students, focused attention on subject-predicate relationships and constituent ordering patterns could help address their higher frequency of word order and missing constituent errors. Lastly, as students' L1 backgrounds significantly affected CSL writing quality, instructors should explain the crosslinguistic transfer effect, acknowledge the influence of L1, and support students in transferring their L1 knowledge into useful L2 writing skills.

6 Conclusions

This study investigated the predictability of linguistic features, including lexical diversity and syntactic complexity, for CSL writing quality as assessed by human raters. The tested linguistic indices, including LTTR for lexical richness and the number of CP per sentence, the mean parse tree depth feature, the mean sentence length, and the NP quantity for syntactic complexity, appear to be powerful predictors to distinguish students' Chinese writing proficiency. Moreover, students' L1 word orders were shown to be a significant background predictor, indicating that SVO-L1 students demonstrated higher Chinese writing proficiency than their SOV-L1 and VSO-L1 peers. These results theoretically enrich the understanding of CSL writing proficiency from lexical and syntactic perspectives, and pedagogically provide targeted guidance for CSL writing instruction and assessment, highlighting the importance of considering students' L1 backgrounds.

Despite the significance of our findings, several limitations warrant attention. This study focused primarily on word order typology and related error patterns, which may underrepresent the broader influences of L1 backgrounds. L1 transfer extends beyond structural domains to rhetorical organization, discourse strategies, cultural approaches to argumentation, and metacognitive writing processes (Wei and Zhang 2020; Xu and Zhu 2024). For instance, cross-cultural preferences in topic development, evidence presentation, and reader–writer stance may substantially affect text quality but remain invisible in the linguistic metrics employed here. Moreover, writing quality may also vary with different learner groups, genres, and topics (Kim et al. 2018; Yang et al. 2015). To address these issues, future research should employ larger and more diverse writing samples and adopt a more comprehensive perspective that integrates structural, rhetorical, cultural, and cognitive dimensions, thereby providing a fuller account of how L1 backgrounds shape CSL writing trajectories.

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Data availability: The data used in this study will be available upon request.

Appendix A

Linguistic levels	Complexity indexes	Measure definition	Examples
Lexical	Average word length	Calculates the average word length in Chinese character. Average word length = total number of characters/total number of words	Lexical example 1 "學校老師於二零二零年九月帶領我和同學們一起參觀了維港薈酒店" AWL = 29 total characters/14 total words = 2.07
	Character richness: corrected TTR	Calculates the type-token ratio for Chinese characters of a text. CTTR = number of character types/sqrt (2*number of tokens)	Same as lexical example 1 CTTR = 26 total character types/$\sqrt{}$(2 × 29 total character tokens) = 3.41
	Character richness: log TTR	Calculates the type-token ratio for Chinese characters of a text. LTTR = Log_{10} (number of character types)/Log10 (number of tokens)	Same as lexical example 1 LTTR = Log_{10} (26 total character types)/Log_{10} (29 total character tokens) = 0.968
	Character richness: root TTR	Calculates the type-token ratio for Chinese characters of a text. RTTR = number of word types/sqrt (number of tokens)	Same as lexical example 1 RTTR = 26 total character types/$\sqrt{}$29 total character tokens = 4.83
	Character richness: uber TTR	Calculates the type-token ratio for Chinese characters of a text. UTTR = (Log number of character types)ˆ2/Log (number of character types/number of tokens)	Same as lexical example 1 UTTR = (Log 29 character types)ˆ2/Log (26 total character types) = 42.60
Syntactic	SD Sentence Length (character) in Tokens	Calculates the standard deviation of sentence length based on Chinese characters in the number of tokens	Syntactic example 2 "酒店有來自世界各地的食材市場、開放式廚房, 落地大玻璃和私人宴會廳。這個酒店的特色是用餐氣氛一流。" Sen_Leng of sentence 1 = 33 characters Sen_Leng of sentence 2 = 15 characters Sen_Leng_SD = 9.0

(continued)

Linguistic levels	Complexity indexes	Measure definition	Examples
	Basic Count of Sentences: Average Sentence Length Based on Characters	Calculates the mean sentence length in Chinese character	Same as syntactic example 2 Sen_Leng of sentence 1 = 33 characters Sen_Leng of sentence 2 = 15 characters
	Mean Parse Tree Depth Feature	Calculates the complexity of the syntax based on the height of the parse tree	Same as syntactic example 2 TDF of sentence 1 = 7 TDF of sentence 2 = 4.5 Mean TDF = 5.75
	Number of Syntactic Constituents: NP	Calculates the number of NP in the text	Same as syntactic example 2 NP_Num in sentence 1 = 5 NP_Num in sentence 2 = 2 Total NP_Num = 7
	Syntactic Complexity Feature: Mean Length of NP	Calculates the mean length of NP NP_Leng = number of words/-number of NP	Same as syntactic example 2 NP_Leng = 16 words/7 NP = 2.29 words per noun phrase
	Number of Syntactic Constituents: CP	Calculates the number of CP in the text	Same as syntactic example 2 CP_Num = 1
	Syntactic Complexity Feature: CP Per Sentence	Calculates the CP per sentence CP/Sen = number of CP/number of sentences	Same as syntactic example 2 CP/Sen = 1 coordinate phrase/2 sentences = 0.5
	POS Density Feature: Conjunction	Calculates conjunction words of the text. Density_Conj = number of conjunction words/number of tokens	Same as syntactic example 2 Density_Conj = 1 conjunction word/48 tokens = 2.1 %
	POS Density Feature: Functional Words	Calculates functional words of the text. Density_Fun = number of functional words/number of tokens	Same as syntactic example 2 Density_Fun = 7 functional words/48 tokens = 0.146
	POS Density Feature: Sentence-final particle	Calculates sentence-final particles of the text. Density_Par = number of sentence-final particles/number of tokens	Same as syntactic example 2 Density_Par = 0

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