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Research Paper

Syntactic Complexity in Professional Architectural Discourse: Insights from Native and Non-native English Speakers' Texts

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Abstract

This study investigates the syntactic differences between texts authored by native (NES) and non-native English-speaking (NNES) professional architects on ArchDaily, the world's most visited architecture website. We focused on established indices of syntactic complexity hypothesized to differentiate between first-language (L1) and second-language (L2) writing. The corpus consisted of randomly selected texts on residential architecture by Iranian and British architects. Data analysis was conducted using Coh-Metrix Core Desktop Beta (2023), with results processed in SPSS. Preliminary MANOVA analysis revealed significant differences in the mean scores of the two groups, and follow-up analyses indicated that syntactic complexity indices, including left-embeddedness, minimal edit distance for words, and the number of modifiers per noun phrase, exhibited medium to large effect sizes in distinguishing the texts. Additionally, among the syntactic density indices, agentless passive voice, negation, gerund, and noun phrase density were most effective in differentiating native from non-native compositions. The findings revealed that while both NES and NNES architects demonstrate sophisticated writing skills, they exhibit distinct patterns of syntactic complexity in their professional discourse. NES architects tend towards richer modification and a more cohesive flow, while NNES architects lean towards longer, denser sentences. These differences, influenced by both linguistic proficiency and discourse-specific conventions, highlight the need for continued attention to clarity and readability in architectural communication and underscore the importance of considering both linguistic proficiency and discourse-semantic motivations when analyzing syntactic complexity in professional writing.

Keywords: Architectural discourse, Coh-Metrix, Second language writing, Syntactic complexity, Syntactic pattern density

According to Crossley and McNamara (2011), L2 writing quality can have important consequences for the authors. Although they put forth this assertion in educational and high-stakes testing contexts, it may be more crucial when readers are specialists in a field and are expected to make vital decisions regarding L2 writers' inclusion in their profession and their

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attainment of socio-economic success (Frantz, Starr, & Bailey, 2015). After reviewing several studies, Crossley and McNamara (2011) concluded that writings evaluated analytically and holistically as higher quality include linguistic sophistication indices such as lexical diversity, word frequency, and syntactic complexity, rather than necessarily facilitating reading rate or comprehension. Bulte and Housen (2018, p.2), however, contend that "linguistic complexity and proficiency do not always increase in parallel and the increase in complexity is neither linear, constant nor guaranteed for all layers (lexical, morphological, and syntactic) and sub-dimensions (e.g. diversity, compositionality, and sophistication)". In academic writing, the increasing formal complexity is driven by the growing functional demand to create more complex conceptual and social meaning within discourse, and as Ortega (2015) states, searching for the functional or discourse-pragmatic motivations of complexity is at least as crucial as formal studies if the full explanation of the developmental trajectory is intended. Ortega suggests that future research on L2 writing should focus more on empirically examining the genre types, L2 writers' prior experiences, and the functional and communicative values of syntactic complexity for L2 writers.

While past research has mainly focused on the descriptive aspects of developmental stages of L2 linguistic complexity in educational and high-stakes testing contexts, few studies have examined the contextually determined demands or the discourse-semantic motivations of linguistic complexity. To address this research gap, the present study examines writing samples from ArchDaily, the world's most visited architecture website, where practitioners from around the world can present their construction projects in English. For practical reasons, the study focused only on indices of syntactic complexity to determine whether there were significant differences between native English-speaking (NES) and non-native English-speaking (NNES) architects' written project presentations. In addition, the findings are discussed in light of discourse-semantic motivations for such variations.

Syntactic Complexity and L2 Development

Research findings usually indicate similar developmental stages for syntactic complexity (Durrant & Brenchley, 2023). Crossley and McNamara (2016), for example, showed that syntactic elaboration is established through clausal coordination, continues with clausal subordination, and completes with clausal and phrasal elaboration mainly at the sentential level. Bulte and Housen (2014) found that, at the end of a 4-month course, all measures of syntactic complexity for L2 intermediate learners (n=49) were significantly higher than their values at the beginning of the study in favor of the assumption that by the end of the study, the learners would produce longer and more complex phrases. Crossley and McNamara (2014) investigated the effect of a semester-long instruction on 70 university-aged L2 learners in an intensive writing class at Michigan State University. The results of three descriptive writing tasks at the beginning, middle, and end of the semester indicated significant growth in complexity, including fewer incidences of all clauses (with the strongest statistical growth), longer noun phrases, less syntactic similarity between sentences (greater variety of constructions), fewer verb phrases, more words before the main verb, and more negation.

Ortega (2015), on the other hand, found some variation in the complexity measures, supporting the idea that it is influenced by factors such as learners' levels and contextual factors. At the intermediate level, for example, the mean number of clauses per T-unit was a better indicator of syntactic complexity. In contrast, at most advanced levels, phrasal elaboration rather than subordination tended to correlate with proficiency. The author concludes that researchers should examine "functional motivations for syntactic complexification attuned for what it may also mean in terms of developmental interfaces with semantic, morphological, and discourse-pragmatic areas of the language that are also subject to developmental explanations" (p.12). The results of Bulte and Housen's (2018) analysis of 10 early-level English L2 learners also indicated that complexity is not parallel to different stages of development, nor is complexity development linear, constant, or similar for all layers of linguistic complexity (lexical, morphological, and syntactic). In other words, L2 writing complexity development exhibited systematic group-level patterns, though it also revealed significant individual variation rather than a uniform or linear progression. It is reminiscent of the idea that L2 development is a multifaceted process, encompassing not only the complexification of syntax but also the concurrent development of a speaker's discourse and sociolinguistic repertoire, which allows language users to adapt their communicative style appropriately to different situational demands and interactional contexts (Ortega, 2003). Regarding such findings, Kyle, Crossley, and Verspoor (2021) proposed a usage-based framework for the development of syntactic complexity, considering syntactic forms and lexical items inseparable in form-meaning pair constructions learned together based on their frequency and saliency in learners' input. Therefore, higher-proficient learners may be predicted to use a higher proportion of lower-frequency lexical items and syntactic structures.

Syntactic Complexity Measures in L2 Writing

Syntactic complexity is usually taken as an index of text quality and L2 development; however, there is no compromise in its measures (Crossley, 2020). According to Kyle, Crossley and Verspoor (2021, p.783), syntactic complexity is typically measured by the mean length of T-unit (MLT), defined by Crossley (2020, p.422) as "the shortest allowable grammatical unit punctuated at the sentence level", mean length of clause (MLC), or the proportion of dependent clauses (DC/C), usually perceived as the measures of language proficiency as well (Kyle & Crossley, 2018). Ortega (2015, p. 83) asserts that "syntactic complexity indexes the expansion of the capacity to use the additional language in ever more mature and skilful ways, tapping the full range of linguistic resources offered by the given grammar to fulfil various communicative goals successfully." In her work, Ortega (2003) focuses on two key factors: 'variety' and 'sophistication.' Here, variety refers to the range of syntactic structures, while sophistication pertains to their complexity. This complexity includes, as Norris and Ortega (2009) state, aspects such as subordination, coordination, phrasal elaboration, and mean length of structures. However, Ortega notes that the concrete definition and application of these concepts can vary across fields. In addition to the previously mentioned measures, more recent research suggests the use of finer-grained indices, such as the number of clauses per T-unit, subordinations, coordinations, passives, infinitives, that-verb complements, and phrasals (Crossley, 2020).

Biber and Gray (2016, p. 11) also list several linguistic features that contribute to the complexity of academic prose, including "technical vocabulary and nominalization, passive voice, attributive adjectives, nouns as pre-modifiers, noun + participles as pre-modifiers, prepositional phrases as nominal post-modifiers, and appositive noun phrases."

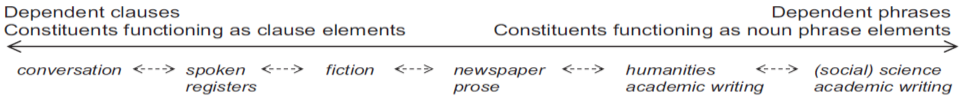
Similarly, Ryshina-Pankova (2015) criticizes the focus on the structural aspects of syntactic complexity as overly simplistic and dismissive of the discourse-semantic motivations behind the phenomena. As she states, the complexity of language forms is a response to contextually determined demands and can only be discussed in terms of the communicative goals they serve. She proposes including Systemic Functional Linguistics (SFL) as a more comprehensive approach to characterizing linguistic complexity, accounting for meaning-based, contextual, and communicative demands.

Syntactic Complexity Variation across Genres and Registers

A comprehensive analysis of linguistic complexity must consider the interplay between genre types (Ortega, 2015) and register analysis (Ryshina-Pankova, 2015) to ensure accurate and contextually relevant interpretations. According to Ortega (2015), different genres are typically characterized by varying levels and indices of complexity. For example, Berman and Nir-Sagiv (2007) found that, unlike narration, expository texts are typically characterized by more advanced lexical and syntactic complexity, including a higher frequency of relative clauses, more complex noun phrases, greater syntactic depth, more abstract head nouns, and more sophisticated modifiers.

Central to Halliday's Systemic Functional Linguistics (SFL) framework for analyzing registers (Halliday, 1994) are three contextual variables: field, mode, and tenor, which refer to the subject matter, channel of communication, and the relationships between interlocutors, respectively. These variables must be considered in the analysis of syntactic complexity (Ryshina-Pankova, 2015). The following diagram shows the cline for clausal and phrasal discourse styles across different fields and registers (Biber & Gray, 2016, p. 141):

Figure 1
Clausal and Phrasal Preference in Different Registers



As it shows, the complexity and sophistication of academic writing are believed to have developed historically in distinct ways across various branches of science. Previous studies have indicated both linguistic similarities and variations among disciplines (Biber & Gray, 2016). For instance, structural elaboration, passive voice, and nominalization are observed in both the sciences and the humanities, while academic prose in the humanities is characterized by more clausal modifications, attributive adjectives, and fewer appositives. In contrast, complexity in pure science is associated with greater structural compression.

Biber and Gray (2016) assert that "structurally compressed grammatical devices or overuse of compressed phrasal devices, nominalizations, nouns as pre-modifiers, and appositives by the authors" (p.18) of science language leads to its unintelligibility to non-experts. However, it is usually considered easy for experts because they can rely on their background technical knowledge to understand it. As mentioned by the authors, other grammatical features responsible for the difficulty of science prose include "the expansion of meaning relationships in noun-noun sequences, increasing noun-participle compounds (e.g., stress-induced anisotropy, health-related problems, GPI-linked protein) and their functionality, and a strong decline in the frequency of finite relative clauses and of-genetive phrases" (p.190). The motive for such linguistic compression comes from the drive towards the economy of expression or the need to use a concise way to present information with the least number of linguistic devices possible (Biber & Gray, 2016); therefore, pre- or post-modifier phrases are preferred to non-finite or finite clauses, while phrasal pre-modifiers are recognized as the most extreme form of compression.

Biber, Gray, and Staples (2016) conducted a systematic analysis of 23 measures of syntactic complexity across spoken and written registers, examining both independent and integrated task types. Their findings revealed systematic linguistic differences in the structural properties of these modalities. Specifically, the researchers observed that reliance on phrasal structures (particularly noun and prepositional phrases) predominantly characterized academic formal writing, whereas spoken registers exhibited a greater prevalence of clausal structures (mainly subordination). This divergence in syntactic complexity profiles between the written and spoken domains highlights the importance of accounting for register variation when analyzing and interpreting patterns of language use.

In line with the issues mentioned above, this study extends previous research by examining contextual variations in syntactic complexity indices and by shedding light on the discourse-semantic motivations underlying these variations to achieve communicative goals. In essence, this study is guided by the following research questions:

1) Are the NES and NNES professional architects' descriptive texts different in terms of syntactic complexity?
2) What discourse-semantic factors motivate such variations?

Method

The study examined the research questions primarily by contrasting two sub-corpora: descriptive texts that present the residential construction projects of leading British architects (as NES authors) versus those of Iranian professional architects (as NNES authors). Later, we used qualitative data analysis to explore potential discourse-semantic motivations for the observed variations in the quantitative data. Alongside this analysis, we provided data samples with brief descriptions, highlighting how specific instances of discourse contribute to understanding these variations.

Corpus

The study's corpus consisted of descriptive texts submitted by architects worldwide to ArchDaily.com, the leading architecture platform attracting over 13.6 million visits each month and operating in five countries (ArchDaily, 2024). The website emphasizes that presenters should ensure the accuracy and quality of their texts prior to submission. Additionally, readers can use the platform's content controllers to select data by country/region and by the nature of architectural projects. For this research, sample texts from leading British architects were selected for comparison with those from Iranian professional architects, specifically focusing on syntactic complexity.

A total of 219 texts were randomly selected from the residential architecture category, the most frequently encountered type of architectural project, comprising 114 texts by native writers and 105 by non-native writers. Other categories, such as high-stakes investment and construction projects, were not included in this research. To meet the requirements of Coh-Metrix analysis, which necessitates clean data (McNamara et al., 2014), the selected texts were reviewed and edited to correct spelling errors and to remove oddities such as images, illustrations, unusual characters, and mathematical symbols.

Analytic Tool

Coh-Metrix, a widely recognized computational tool, was used to measure syntactic complexity indices because it provides speed, flexibility, and reliability (Crossley & McNamara, 2014). Previous research has also affirmed the tool's reliability and validity across multiple studies (e.g., Crossley & McNamara, 2009; Dowell, Graesser, & Cai, 2016; Hempelmann, Rus, Graesser, & McNamara, 2006; McNamara, Louwerse, McCarthy, & Graesser, 2010). For data collection in the current study, we used the most recent version of

Coh-Metrix, the Coh-Metrix Core Desktop Beta (2023) package. The table below (Table 1) presents a compilation of Coh-Metrix indices, along with their corresponding codes and descriptions (McNamara et al., 2014, pp. 247-251). To ensure the inclusion of all theoretically and operationally relevant items as required for the analysis (Crossley & Kim, 2022), we included all syntactic complexity indices in the preliminary analysis. However, following the guidelines provided by Crossley and McNamara (2014), we focused only on those indices that measure clausal and phrasal-level syntactic features. The included indices comprised incidence counts derived from the Charniak (2000) part-of-speech tagger/parser (normalized for text length), ratio scores, raw scores, and length counts.

Table 1

Coh-Metrix Indices of the Study

	Label in Coh-Metrix	Description
Syntactic Complexity Indices		
1	SYNLE	Left embeddedness, words before the main verb, mean
2	SYNNP	Number of modifiers per noun phrase, mean
3	SYNMEDpos	Minimal Edit Distance, part of speech
4	SYNMEDwrd	Minimal Edit Distance, all words
5	SYNMEDlem	Minimal Edit Distance, lemmas
6	SYNSTRUTa	Sentence syntax similarity, adjacent sentences, mean
7	SYNSTRUTt	Sentence syntax similarity, all combinations, across paragraphs, mean
Syntactic Pattern Density		
1	DRNP	Noun phrase density, incidence per 1000 words
2	DRVP	Verb phrase density, incidence per 1000 words
3	DRAP	Adverbial phrase density, incidence per 1000 words
4	DRPP	Preposition phrase density, incidence per 1000 words
5	DRPVAL	Agentless passive voice density, incidence per 1000 words
6	DRNEG	Negation density, incidence per 1000 words
7	DRGERUND	Gerund density, incidence per 1000 words
8	DRINF	Infinitive density, incidence per 1000 words

Seven items under the syntactic complexity category and eight items as syntactic density patterns represent the overall syntactic complexity measure (Lu, 2017). Items of the first group suggest that higher frequency of modifiers, degree of embeddedness, and semantic and syntactic dissimilarity indices are indicative of higher degrees of syntactic complexity; moreover, higher incidence of NPs, VPs, APs, PPs, passive voice, negation and verb conjugations (infinitive and gerund) suggests denser informational content which is more difficult to process (McNamara et al., 2014).

As Lu (2017) states, the first two measures, SYNLE and SYNNP, assume that "syntactically complex sentences tend to include embedded constituents and are often structurally dense" (p. 502). Higher values of the SYNLE and SYNNP indices represent greater complexity of the structures by computing higher degrees of left embeddedness and embeddedness of noun phrases, respectively. However, higher values of the next five measures indicate "higher degrees of uniformity of the syntactic constructions in the texts, resulting in less complex syntax that is easier to process" (p. 502). In general, syntactic complexity is characterized by a higher proportion of embedded constituents, which are usually more difficult to process and comprehend (Crossley & McNamara, 2011).

Results

A one-way MANOVA was performed to test for statistically significant mean differences across the individual indices that comprise syntactic complexity and syntactic density patterns, with descriptive statistics summarized in the following table.

Table 2

Descriptive Statistics of the Groups

	Grouping	N	Mean	Std. Deviation	Std. Error Mean
SYNLE	Non-native	105	6.882981	3.0482315	.2974769
	Native	114	5.118746	1.9324412	.1809897
SYNNP	Non-native	105	1.284981	.1713833	.0167253
	Native	114	1.481947	.1557593	.0145882
SYNMEDpos	Non-native	105	.577971	.0482676	.0047104
	Native	114	.576430	.0381571	.0035737
SYNMEDwrd	Non-native	105	.856724	.0312375	.0030485
	Native	114	.869746	.0283142	.0026519
SYNMEDlem	Non-native	105	.835810	.0322652	.0031488
	Native	114	.851026	.0266676	.0024976
SYNSTRUTa	Non-native	105	.079790	.0225225	.0021980
	Native	114	.083868	.0235810	.0022086
SYNSTRUTt	Non-native	105	.078810	.0205595	.0020064
	Native	114	.080526	.0161526	.0015128
DRNP	Non-native	105	375.616677	31.8484853	3.1080939
	Native	114	348.192676	26.3722052	2.4699833
DRVP	Non-native	105	158.069886	26.5274957	2.5888185
	Native	114	164.876079	26.6244924	2.4936122
DRAP	Non-native	105	15.555600	9.1051352	.8885702
	Native	114	17.288640	8.2852938	.7759889
DRPP	Non-native	105	146.071933	21.7206130	2.1197148
	Native	114	124.995482	14.8401312	1.3899056
DRPVAL	Non-native	105	15.931819	8.1469233	.7950583
	Native	114	12.822263	5.9359083	.5559487
DRNEG	Non-native	105	2.470762	2.7214575	.2655871
	Native	114	1.153482	1.8579110	.1740093
DRGERUND	Non-native	105	22.211895	10.5060525	1.0252857
	Native	114	27.547070	11.3154365	1.0597877
DRINF	Non-native	105	16.520867	9.8225788	.9585855
	Native	114	15.042439	7.1286232	.6676567

Table 2 presents descriptive statistics for the study's key variables, including the means and standard deviations for syntactic complexity and density measures. These differences suggest that further inferential statistical analysis is necessary to determine the significance of the observed variations.

Preliminary assumption testing was conducted to assess normality, linearity, univariate and multivariate outliers, homogeneity of variance-covariance matrices, and multicollinearity, leading to some modifications to the data, as suggested by Pallant (2020). First, the dependent variables were checked for multicollinearity and high correlations, and strongly correlated pairs were removed. As predicted by McNamara et al., (2014), a very high correlation (r =.937, p<.001) was observed between SYNMEDwrd and SYNMEDlem (see the appendix for the table of correlations). Therefore, in order to avoid singularity or having too similar dependent variables, SYNMEDwrd was retained, and SYNMEDlem was removed from the list of dependent variables because SYNMEDwrd seemed to provide more surface-level analysis of the syntactic complexity. Checking multivariate normality and outliers was done using the Mahalanobis distance (see the table of residual statistics in the appendix). The maximum value for Mahalanobis distance in the table is 36.172, while the critical value for six dependent variables is 22.46 (Pallant, 2020, p.280). The critical value was used as a guideline to remove five items with values exceeding 22.46 as multivariate outliers from the data. Linearity, or the presence of a straight line between each pair of dependent variables, was assessed using a matrix of scatterplots (see the appendix for the scatterplots). To assess the homogeneity of variance-covariance matrices, the Box's M Test of Equality of Covariance Matrices was consulted, and the results (see in the appendix) indicated the violation of this assumption. Therefore, several measures were taken to compensate for the violation, including choosing a more conservative alpha level (α = 0.01 instead of 0.05), referring to Wilk's Lambda, which is less sensitive to the assumption violations, and performing separate univariate ANOVAs on each dependent variable to avoid Type I error (see the appendix).

Table 3

Multivariate Tests of Complexity Measures

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
groups	Pillai's Trace	.363	19.678b	6.000	207.000	.000	.363
	Wilks' Lambda	.637	19.678b	6.000	207.000	.000	.363
	Hotelling's Trace	.570	19.678b	6.000	207.000	.000	.363
	Roy's Largest Root	.570	19.678b	6.000	207.000	.000	.363

As shown in the table, there was a statistically significant difference between NES and NNES architects on the combined dependent variables, F (2, 214) = 19.678, p<.001; Wilks' Lambda=.637; partial eta squared = .363.

Table 4

Tests of Between-Subjects Effects for Complexity Measures

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
groups	SYNLE	127.346	1	127.346	23.192	.000	.099
	SYNNP	2.108	1	2.108	79.720	.000	.273
	SYNMEDpos	2.451	1	2.451	.015	.901	.000
	SYNMEDwrd	.011	1	.011	13.656	.000	.061
	SYNSTRUTa	.000	1	.000	.668	.415	.003
	SYNSTRUTt	5.381	1	5.381	.162	.688	.001

According to the table, when the dependent variables were considered separately, SYNLE, SYNNP, and SYNMEDwrd showed a statistically significant difference in the means between NES and NNES writers. According to Cohen's guidelines (Pallant, 2020, p.208), however, partial eta-squared values indicated a medium effect size for SYNLE (.099) and SYNMEDwrd (.061) and a large effect size for SYNNP (.27).

A similar assumption test was conducted to check the syntactic density pattern indices. Unlike syntactic complexity indices, no variables showed correlations that were too high, so the variables remained untouched (see the correlation table in the appendix). Checking multivariate normality and outliers was performed using the Mahalanobis distance (see the table of residual statistics in the appendix). The maximum value for Mahalanobis distance in the table was 61.6282, while the critical value for eight dependent variables was 26.13 (Pallant, 2020, p.280). The critical value was used as a guideline to remove eight items with values exceeding 26.13 as multivariate outliers from the data. Linearity and the homogeneity of variance-covariance matrices were assessed with a matrix of scatterplots and the Box's M Test of Equality of Covariance Matrices, respectively (see the appendix for the tables).

Table 5

Multivariate Tests of Syntactic Density Measures

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
groups	Pillai's Trace	.493	23.971	8.000	197.0	.000	.493
	Wilks' Lambda	.507	23.971	8.000	197.0	.000	.493
	Hotelling's Trace	.973	23.971	8.000	197.0	.000	.493
	Roy's Largest Root	.973	23.971	8.000	197.0	.000	.493

As shown in the table, there was a statistically significant difference between NES and NNES architects on the combined dependent variables, F (2, 206) = 23.971, p<.001; Wilks' Lambda= .507; partial eta squared = .493.

Table 6

Tests of Between-Subjects Effects for Density Measures

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
groups	DRNP	32803.256	1	32803.256	41.814	.000	.170
	DRVP	2436.804	1	2436.804	3.801	.053	.018
	DRAP	271.753	1	271.753	4.063	.045	.020
	DRPP	20643.397	1	20643.397	76.929	.000	.274
	DRPVAL	607.953	1	607.953	15.011	.000	.069
	DRNEG	98.546	1	98.546	20.380	.000	.091
	DRGERUND	2304.748	1	2304.748	23.055	.000	.102
	DRINF	80.068	1	80.068	1.398	.238	.007

According to the table, when the results of dependent variables were considered separately, DRNP (F=41.814, p<.001), DRPP (F=76.929, p<.001), DRPVAL (F=15.011, p<.001), DRNEG (F=20.380, p<.001), DRGERUND (F=23.055, p<.001) indicated statistically significant differences between the means of NES and NNES writers. The table indicates that NNES writers employed significantly more noun phrases, prepositional phrases, passive constructions, and negation, whereas NES writers employed significantly more gerunds. According to Cohen's guidelines (Pallant, 2020, p.208), however, partial eta-squared values indicated a medium effect size for DRPVAL (.069), DRNEG (.091), and DRGERUND (.102) and a large effect size for DRNP (.17) and DRPP (.274).

Discussion

One objective of the present study was to contrast the syntactic complexity measures of the descriptive texts of NES and NNES professional architects published on ArchDaily, the most prominent architecture website with more than 13.6 million monthly visits. The first part of the statistical analysis identified significant differences in the means of the different indices, including the frequency of modifiers, degree of embeddedness, and sentence construction uniformity and consistency. It involved NES architects' higher values of SYNNP and SYNMEDword and NNES architects' higher values for SYNLE. SYNNP, or average number of modifiers per noun-phrase, is an index of syntactic complexity which enhances as proficiency develops, so achieving higher values by NES authors seems to be in line with developmental studies of syntactic complexity (e.g. Bulte & Housen, 2014; Crossley & Kim, 2022; Crossley & McNamara, 2014; Crossley & McNamara, 2016; Ortega, 2015). In other words, NES architects are naturally more proficient and have access to richer linguistic input (Jagaiah, Olinghouse, & Kearns, 2020). The results may suggest the same interpretation for SYNMEDword or minimal edit distance for words, which identifies "the distance that words are from one another between consecutive sentences in the text…and tends to correlate with referential and semantic cohesion and syntactic complexity strongly" (McNamara et al., 2014, p.70).

The higher mean of SYNLE observed among NNESs, which may seem counterintuitive to findings from some previous research (Hinkel, 2003) and to our expectations, indicates their high language proficiency in constructing complex, lengthy structures by incorporating elements such as phrases and clauses before the main verbs. While this adeptness can be an advantage for NNES writers, several considerations must be taken into account. First, participation by architects in submitting project descriptions to ArchDaily requires a high level of language proficiency, and all contributors, including NNESs, are aware that the submission process demands strong writing skills. This context underscores our exploration of the nuanced syntactic structure differences between the two groups. Second, in many instances, NNES experts and authors represent distinct groups that collaborate to produce texts. While we lacked information regarding whether these texts were generated by the authors themselves or by hired professional translators or language experts, an excessive emphasis on complexity through syntactic embedding may stem from a profound mastery of the language or an attempt to demonstrate their command of English even at the expense of readability.

This is where we attempted to answer the second research question by investigating the discourse-semantic motivations underlying the observed differences. Prioritizing thoroughness in descriptions could also stem from factors such as NNESs' native culture and linguistic background preferences, as well as from an aim to create a more formal and objective tone (Austin, 1998; Parviz, Jalilifar, & Don, 2024). If the texts are translated from another language, the syntactic structures of the original language might also influence the English translation. Correspondingly, Xu and Li (2021) analyzed syntactic complexity in translational versus non-translational English across four genres- academic, general prose, news, and literary texts- and found that translational English was significantly more complex in thirteen of fourteen complexity indices. In addition, the interpretation of statistical results without considering contextually relevant discourse-semantic motivations can be overly simplistic (Ortega, 2015; Ryshina-Pankova, 2015). For example, the argumentative genre, unlike other genres, requires higher levels of syntactic complexity depending on factors such as topic, writing function, and audience (Jagaiah, Olinghouse, & Kearns, 2020). These motivations might influence their syntactic choices, leading to longer sentences with higher values for embeddedness.

SYNNP, or average number of modifiers per noun phrase, may indicate the writers' attempt to create a detailed and vivid description of architectural elements, as shown in the following examples of both groups.

NES sample: It comprises *a 15-storey office building* that hosts the *London headquarters* for Amazon, alongside one of *London's tallest residential buildings*, *the 50-storey Principal Tower*, with *six eateries* that wrap around the building at *street level* and *a light bar*, creating *a 360-degree active frontage* that extends the vibrancy of the City towards the north (Foster+Partners, 2025).

NNES sample: A stack of *four cubes*, Zomorrod 11 stands firmly at the heart of *a traffic junction* in Tehran. The design incorporates geometric brick pattern modules, following a strategy in which the exterior façade of the building extends inside and forms many elements of the interior, from *the lowest parking level* at -5 through to the top (Acaran Architects, 2025).

As indicated by the examples, favoring complexity and detail by using extensive NP modifiers (shown in italics) is the norm in the architectural community, and NES architects may be more skilled at aligning their writing with such conventions.

NESs' higher mean of SYNMEDword may also suggest their sensitivity to creating smoother transitions for clearer connections between the ideas and their intention to maintain a consistent and coherent writing style, while NNESs may exhibit more variability in their word choices, which could potentially affect the overall fluency and cohesiveness of their texts (Scarcella, 1984).

NNESs' mean of SYNLE, however, was significantly higher than NESs'. As evident in the following examples, this suggests that NNES writers also recognized that detailed descriptions and specifications are valued in architecture and consciously included complex structures before the main verb. However, creating very long constructions may result in reduced clarity, potential misunderstandings, and increased cognitive load for readers (Kintsch, 1998).

NNES sample: The *architects' priority to use locally sourced and environmentally conscious materials* led them to explore brick-laying patterns for a façade that is both iconic and unique, and which separates itself from the construct of being old-school or generically vernacular (Zad, Ashrafi, & Marizad, 2024).

NES sample: *The relationship between the creative, formerly industrial East End and London's financial center* is expressed in the tower's massing, which appears as three slim volumes (Foster+partners, 2025).

The second part of the statistical analysis revealed significant differences in the densities of particular syntactic patterns, word types, and phrase types, providing further insight into the syntactic complexity of the texts. NNES writers' texts exhibited a higher DRNP, DRPP, DRPVAL, and DRNEG incidence, while NES' DRGERUND incidence was significantly higher. The results seem to contradict previous research aimed at discerning differences between NES and NNES writing. Wang, Anthony and Arshad (2023), for example, reported that language experts' mean scores on syntactic sophistication indices such as DRPP were significantly higher than those of non-native language learners. The following examples from NES and NNES texts illustrate the authors' language mastery and their use of various syntactic patterns, making it challenging to discern differences in complexity solely from the excerpts. However, statistical analysis revealed subtle nuances in these variations:

NES sample: The 50-storey building offers a variety of apartment sizes, topped by spectacular penthouses on the top. Designed from the inside out, there are eight apartments on a typical floor: four two-bedroom apartments in the main corners of the plan and four one-bedroom apartments. The square floorplate has been extended along the center of two sides to create a cruciform plan and, most importantly, eight corners, each forming a curved balcony. By maximizing the perimeter in this way, all units on typical floors have dual-aspect views, with a very efficient plan that places the entrance at the heart of the apartment, eliminating unnecessary corridors. Solid cladding panels for privacy enclose the bedrooms, while the remainder of the apartment is fully glazed and protected by shading fins (Foster + Partners, 2025).

NNES sample: The use of different materials was minimized in order to create a homogenous and harmonized mass in the urban scenery. Therefore, the entire building façade was covered by traditional brick with green-blue glazed bricks on the flower boxes to put more emphasis on this vertical landscape. Mechanical equipment was placed in the space under the flowerboxes, making the best of this otherwise useless space. Staircases are usually not popular and are less used in residential buildings. In this project, the staircase has been prioritized and brought to the front façade, making it pleasant to use as an everyday exercise (Hooba Design, 2025).

To explain the discourse-semantic causes of these variations, we must recognize that the necessity of using syntactically complex sentences might not apply universally across different writing styles or genres. Factors such as the topic, purpose of the writing, and audience create varying syntactic requirements for the author (Jagaiah, Olinghouse, & Kearns, 2020; Lu, 2011). Blair and Crump (1984), for example, found that complex and compound/complex sentences were more commonly used in the argumentative mode, whereas simple and compound sentences were more prevalent in the descriptive mode, reinforcing the idea that descriptive writing typically requires less complexity than argumentative writing. The results support the notion that when NNES texts are characterized by greater informational density and more complex syntax, they may pose greater processing challenges for the readers (McNamara et al., 2014). In other words, NNES's overestimation or underestimation of the audience's expectations and tolerance for syntactic complexity can lead to syntactic choices that are either overly simplistic or unnecessarily sophisticated (Huang, 2011). On the other hand, tailoring the complexity to match the audience's expected level of detail and complexity helps maintain their engagement and prevents them from being overwhelmed.

Conclusion

In conclusion, this study has illuminated nuanced differences in the syntactic complexity of architectural discourse produced by NES and NNES professionals, extending beyond mere linguistic proficiency. Aligning with rhetorical expectations of clarity and conciseness, often valued in English-speaking contexts, NES architects demonstrated a greater tendency to use noun phrase modification and cohesive sentence structures, while NNES architects tended to construct longer, syntactically dense sentences. This latter pattern, while potentially indicative of advanced language command, may also reflect different rhetorical strategies, cultural communication styles that prioritize thoroughness, or even the influence of translation practices; however, such speculations require further qualitative investigation, which is beyond the scope of this paper.

The observed inclination among NNES architects towards lengthy, densely structured sentences raises important implications for clarity and accessibility in professional communication, potentially increasing readers' cognitive load, even within a specialized audience. Therefore, architectural educators and practitioners should be mindful of these potential challenges and promote a balanced approach that values both syntactic sophistication and readability.

Further research should address limitations inherent in this study, such as the reliance on a single online platform and the lack of detailed author demographics, by examining a wider range of text sources and incorporating participant background information. While exploring ArchDaily's texts provides insights into contemporary residential architecture, it is crucial to note that these insights may not be generalizable beyond this narrow scope. Future research could benefit from expanding the dataset to include a wider range of architectural texts, thereby enriching our understanding of the field as a whole. Future investigations could also explore the impact of these syntactic variations on reader comprehension through empirical studies, assess the role of translation in shaping syntactic complexity, and evaluate the effectiveness of targeted interventions to enhance the clarity and conciseness of NNES architects' writing. Ultimately, a deeper understanding of the interplay among linguistic proficiency, rhetorical conventions, cultural influences, and stylistic choices is crucial for fostering more effective and inclusive communication within the global architectural community and promoting broader access to architectural knowledge and innovation.

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Appendix

		SYNLE	SYNNP	SYNMEDpos	SYNMEDwrd	SYNMEDlem	SYNSTRUTa	SYNSTRUTt
SYNLE	Pearson Correlation	1	-.146*	-.154*	-.277**	-.273**	-.182**	-.193**
	Sig. (2-tailed)		.031	.023	.000	.000	.007	.004
	N	219	219	219	219	219	219	219
SYNNP	Pearson Correlation	-.146*	1	-.183**	.051	.046	.211**	.145*
	Sig. (2-tailed)	.031		.007	.456	.495	.002	.032
	N	219	219	219	219	219	219	219
SYNMEDpos	Pearson Correlation	-.154*	-.183**	1	.604**	.616**	-.272**	-.191**
	Sig. (2-tailed)	.023	.007		.000	.000	.000	.005
	N	219	219	219	219	219	219	219
SYNMEDwrd	Pearson Correlation	-.277**	.051	.604**	1	.937**	-.014	.035
	Sig. (2-tailed)	.000	.456	.000		.000	.832	.609
	N	219	219	219	219	219	219	219
SYNMEDlem	Pearson Correlation	-.273**	.046	.616**	.937**	1	-.077	.001
	Sig. (2-tailed)	.000	.495	.000	.000		.254	.982
	N	219	219	219	219	219	219	219
SYNSTRUTa	Pearson Correlation	-.182**	.211**	-.272**	-.014	-.077	1	.772**
	Sig. (2-tailed)	.007	.002	.000	.832	.254		.000
	N	219	219	219	219	219	219	219
SYNSTRUTt	Pearson Correlation	-.193**	.145*	-.191**	.035	.001	.772**	1
	Sig. (2-tailed)	.004	.032	.005	.609	.982	.000	
	N	219	219	219	219	219	219	219

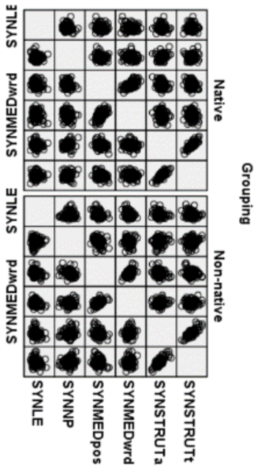
*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.23	1.41	.52	.301	219
Std. Predicted Value	-2.494	2.952	.000	1.000	219
Standard Error of Predicted Value	.034	.168	.069	.023	219
Adjusted Predicted Value	-.25	1.44	.52	.304	219
Residual	-.890	.923	.000	.400	219
Std. Residual	-2.192	2.273	.000	.986	219
Stud. Residual	-2.279	2.312	-.002	1.002	219
Deleted Residual	-.962	.955	-.002	.414	219
Stud. Deleted Residual	-2.302	2.336	-.003	1.005	219
Mahal. Distance	.527	36.172	5.973	5.274	219
Cook's Distance	.000	.074	.005	.009	219
Centered Leverage Value	.002	.166	.027	.024	219

a. Dependent Variable: Grouping



Box's Test of Equality of Covariance Matrices[a]

Box's M	49.427
F	2.283
df1	21
df2	162276.961
Sig.	.001

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + group2

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
SYNLE	Between Groups	127.346	1	127.346	23.192	.000
	Within Groups	1164.073	212	5.491		
	Total	1291.419	213			
SYNNP	Between Groups	2.108	1	2.108	79.720	.000
	Within Groups	5.605	212	.026		
	Total	7.713	213			
SYNMEDpos	Between Groups	.000	1	.000	.015	.901
	Within Groups	.336	212	.002		
	Total	.336	213			
SYNMEDwrd	Between Groups	.011	1	.011	13.656	.000
	Within Groups	.169	212	.001		
	Total	.180	213			
SYNMEDlem	Between Groups	.015	1	.015	19.107	.000
	Within Groups	.165	212	.001		
	Total	.179	213			
SYNSTRUTa	Between Groups	.000	1	.000	.668	.415
	Within Groups	.100	212	.000		
	Total	.100	213			
SYNSTRUTt	Between Groups	.000	1	.000	.162	.688
	Within Groups	.071	212	.000		
	Total	.071	213			

Correlations

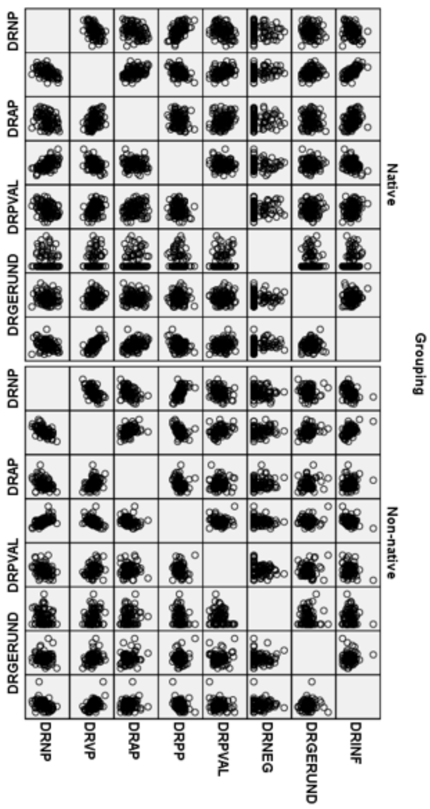
		DRNP	DRVP	DRAP	DRPP	DRPVAL	DRNEG	DRGERUND	DRINF
DRNP	Pearson Correlation	1	-.540**	-.374**	.649**	-.194**	.010	-.166*	-.291**
	Sig. (2-tailed)		.000	.000	.000	.004	.889	.015	.000
	N	214	214	214	214	214	214	214	214
DRVP	Pearson Correlation	-.540**	1	.380**	-.438**	.309**	.153*	.265**	.575**
	Sig. (2-tailed)	.000		.000	.000	.000	.025	.000	.000
	N	214	214	214	214	214	214	214	214
DRAP	Pearson Correlation	-.374**	.380**	1	-.218**	.106	.072	.092	.249**
	Sig. (2-tailed)	.000	.000		.001	.121	.295	.179	.000
	N	214	214	214	214	214	214	214	214
DRPP	Pearson Correlation	.649**	-.438**	-.218**	1	.042	.002	-.074	-.252**
	Sig. (2-tailed)	.000	.000	.001		.537	.982	.278	.000
	N	214	214	214	214	214	214	214	214
DRPVAL	Pearson Correlation	-.194**	.309**	.106	.042	1	.046	.004	.002
	Sig. (2-tailed)	.004	.000	.121	.537		.507	.956	.978
	N	214	214	214	214	214	214	214	214
DRNEG	Pearson Correlation	.010	.153*	.072	.002	.046	1	-.085	.086
	Sig. (2-tailed)	.889	.025	.295	.982	.507		.215	.208
	N	214	214	214	214	214	214	214	214
DRGERUND	Pearson Correlation	-.166*	.265**	.092	-.074	.004	-.085	1	.021
	Sig. (2-tailed)	.015	.000	.179	.278	.956	.215		.758
	N	214	214	214	214	214	214	214	214
DRINF	Pearson Correlation	-.291**	.575**	.249**	-.252**	.002	.086	.021	1
	Sig. (2-tailed)	.000	.000	.000	.000	.978	.208	.758	
	N	214	214	214	214	214	214	214	214

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.40	1.33	.52	.350	214
Std. Predicted Value	-2.630	2.312	.000	1.000	214
Standard Error of Predicted Value	.034	.198	.071	.023	214
Adjusted Predicted Value	-.56	1.36	.52	.354	214
Residual	-.789	.856	.000	.358	214
Std. Residual	-2.165	2.349	.000	.981	214
Stud. Residual	-2.206	2.407	-.002	1.002	214
Deleted Residual	-.819	.899	-.002	.373	214
Stud. Deleted Residual	-2.227	2.435	-.002	1.005	214
Mahal. Distance	.818	61.628	7.963	6.998	214
Cook's Distance	.000	.078	.005	.010	214
Centered Leverage Value	.004	.289	.037	.033	214



Box's Test of Equality of Covariance Matrices[a]

Box's M	63.422
F	1.688
df1	36
df2	131547.971
Sig.	.006

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + group2