

Exploring Lexical Richness in English-Language theses Across Disciplines: A Comparative Analysis

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ABSTRACT

This study investigates the variations in lexical richness within English language theses across diverse disciplines, focusing on areas where researchers exhibit higher degrees of lexical richness and the evolution of vocabulary usage over time. By analyzing these variations, the research aims to provide insights into the effective use of lexical richness in academic writing and contribute to the development of more engaging and comprehensible scholarly publications. A total of 320 theses were randomly selected from the Turkey National Thesis Center and classified according to their scientific discipline. Using natural language processing techniques, unique word count, word diversity, and other metrics were analyzed. Results reveal that social sciences tend to exhibit higher lexical richness compared to natural sciences, and no significant difference was observed in word richness between social and natural sciences disciplines. These findings contribute to the understanding of lexical richness in academic writing and highlight the importance of achieving a balance between lexical richness and readability.

Keywords: Lexical Richness, Academic Theses, Artificial Neural Networks, Stanford-NLP, Text Mining.

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INTRODUCTION

In academic writing, a well-crafted language characterized by a high degree of lexical richness greatly aids readers in achieving better comprehension, becoming more persuasive and impactful, and even altering their attitudes and behaviors through the evocation of their emotions. The extent of lexical richness, encompassing the employment of diverse terminologies, intricate sentence structures, and a wide-ranging vocabulary, profoundly influences the caliber of scholarly publications.^[1]

Clarity and readability are of paramount importance in academic publications, as these works are frequently aimed at a heterogeneous readership representing a myriad of backgrounds. Consequently, the judicious application of lexical richness is essential in facilitating a reader's comprehension of the text. Incorporating an array of sentence structures and an advanced vocabulary can further augment the reader's grasp of the subject matter.

Scholarly publications are typically the medium for the presentation of novel ideas and groundbreaking discoveries.

Employing a high degree of lexical richness enables authors to articulate these innovative concepts in a unique and captivating manner, ultimately leading to more engaging and thought-provoking contributions to the academic community. In the realm of academic writing, the accuracy and expressiveness of an author's ideas are of utmost significance.^[2] An elevated level of lexical richness permits authors to effectively communicate their thoughts, thereby enhancing the reader's understanding.

It is imperative to strike a balance between lexical richness and readability in academic writing. An overabundance of lexical richness can render a publication challenging to comprehend, ultimately leading to reader fatigue. On the other hand, employing a limited vocabulary may cause the publication to appear monotonous and uninspiring. Attaining the optimal equilibrium between lexical richness and readability is crucial for generating high-quality academic writing.

The primary objective of this study is to examine the variation in lexical richness within English language theses across a diverse array of disciplines. The research emphasizes disciplines in which researchers exhibit a higher degree of lexical richness, as well as the evolution of vocabulary usage over time. The objective of this research is to gain a deeper understanding of how lexical diversity can be effectively utilized in academic writing, with the ultimate goal of enhancing the quality and readability of scholarly publications through valuable insights.



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RELATED STUDIES

Natural Language Processing (NLP) has emerged as a prominent area of academic research in recent years.^[3-5] The vast availability of natural language data, particularly through the internet and social media platforms, has facilitated the development of NLP models based on large datasets and the exploration of diverse patterns, structures, and relationships within natural language.^[6,7] Artificial intelligence and machine learning techniques are widely employed in NLP research, enabling the creation of algorithms capable of processing extensive datasets and autonomously learning language models.

NLP can be utilized in a multitude of applications, such as machine translation, text classification, sentiment analysis, speech recognition, word suggestions, and dialogue systems. Consequently, NLP research can be applied across various domains, fostering the development of more effective and efficient language processing models. Lexical richness and language quality are vital components of NLP research, with lexical richness serving as a measure of the richness and diversity of natural language.^[8]

Several academic methods are available for measuring lexical richness. Heaps' Law posits that the number of unique words in a document is proportional to the total word count raised to a specific power, providing more detailed information on lexical richness.^[9,10] The Shannon-Weaver Index employs entropy as a natural measure of word distribution, offering insights into not only lexical richness but also the regularity of word distribution. The n-gram method measures lexical richness by counting word combinations within a specific sequence of words.^[11,12]

Dictionary-based methods offer a simple and rapid approach to measuring lexical richness but overlook the varying importance of individual words and the potential for multiple meanings. The unique word count method calculates the number of unique words in a document, providing a straightforward and swift measure, albeit with limitations similar to those of dictionary-based methods. The Type-Token Ratio (TTR) computes the ratio of unique words to the total word count in a document, providing more comprehensive information on lexical richness.^[13]

The Guiraud Index calculates the ratio of unique words in a document to the square root of the document's total word count, providing more in-depth insights into lexical richness and accounting for the relationship between unique word count and document length. The Herdan Index determines the ratio of unique words in a document to half of the document's total word count, offering detailed information on lexical richness and considering the relationship between unique word count and document length. The lexical richness of senior students was investigated by comparing their written works to academic papers authored by their lecturers.^[13] The analysis revealed that

lecturers performed better in terms of Type-Token Ratio (TTR) and academic vocabulary usage, while students demonstrated a slightly higher usage of 2000-word level and off-list words. Joe^[14] tracked the quality and quantity of encounters with 20 vocabulary items experienced by adult Second-Language (L2) learners over a 3-month period in an English for Academic Purposes course. The differences in vocabulary choices between Chinese master's degree candidates and advanced writers displayed a higher level of lexical richness and complexity.^[15] The lexical richness in research articles published by English as a Second Language (ESL) and English as a Foreign Language (EFL) writers from ASEAN countries has been determined to reveal the presence of significant similarities and differences between the two groups in terms of lexical richness.^[16] To answer this question, the researchers employed three different lexical measures: lexical density, lexical diversity, and lexical sophistication. Utilizing analytical tools such as the CLAWS Tagger, Moving-Average Type-Token Ratio (MATTR), and VocabProfiler, they analyzed the data and compared the results between ESL and EFL groups using the Mann-Whitney U test. This study also discussed the factors influencing word usage by both groups and concluded with the study's limitations and directions for future research.

The relationship between text length and lexical richness from an entropy-based perspective are examined in a study.^[17] Their findings indicated a nonlinear growth model for lexical richness as text length increased. Kim's study compared the lexical richness, specifically lexical diversity, density, and complexity, in research article manuscripts prepared by Chinese doctoral candidates (PhD-Candidate) to those written by native undergraduate and master's level students (Native Beginner Students, NBS) as well as published and unpublished research articles. In a study discuss methods for measuring linguistic richness from a linguist's perspective.^[18] Assessing the scope and richness of a language is not an area of study exclusive to the English language. Word richness analysis are done in textual documents for French, German, and Portuguese languages in academic studies,^[19] while a study^[20] focused on French, and other study^[21] explored the Turkish language in same matter.

DATA ANALYSIS AND PROPOSED METHOD

A master's thesis aims to facilitate the student's in-depth research in their field of study, enabling them to acquire comprehensive knowledge on their thesis topic and contribute creatively within the discipline. The thesis typically spans 50-100 pages and encompasses an extensive literature review, research methodology, results, discussion, and recommendations. A doctoral dissertation, on the other hand, entails a more extensive research endeavor compared to a master's thesis. Doctoral students engage in interdisciplinary, high-level research to creatively address or uncover new findings within their discipline. Doctoral dissertations are generally 200-300 pages long, incorporating

an extensive literature review, research methodology, results, discussion, recommendations, an introduction reflecting the student's broad research and knowledge within the discipline, and a preface summarizing the topics presented in the thesis.

Both master's and doctoral theses offer opportunities for students to showcase their in-depth mastery of the subject matter and contribute to the scientific community in their respective disciplines. They also aid in the development of students' research methodology application, analysis, interpretation, and reporting skills. Theses necessitate academic writing style and language usage, adhering to grammar and writing rules, and employing scientific and technical language.

Lexical richness in theses is a crucial factor, reflecting the researcher's command of the subject, analytical thinking ability, and writing skills.^[22] Emphasis should be placed on lexical diversity rather than merely the number of words used. Lexical richness signifies the researcher's expertise in the subject, as they must select appropriate words to convey their ideas. Word choice demonstrates the researcher's familiarity with the topic, and their analytical thinking ability, as they must approach the subject from various angles and select words to express their ideas accurately.

Moreover, lexical richness is essential in terms of thesis quality.^[23] Lexical diversity renders the thesis more varied and engaging, while preventing word repetition, ensuring a smooth and comprehensible flow. The characteristics of a scientific subject can influence the lexical richness employed within a thesis. For instance, some scientific topics, particularly those that are technical and abstract, involve fewer common terms and phrases. While such topics necessitate a higher degree of lexical richness, it is also crucial to maintain clarity by using more straightforward and accessible language. Conversely, more general and widely understood topics require less technical terminology and simpler lexical structures.

There are numerous methods for text classification within data mining, including the following:

Naïve Bayes Classification

This algorithm determines whether a text belongs to a particular category by calculating the probability of each word in a given sequence. Naïve Bayes classification is one of the most commonly used methods for text classification.^[24]

Decision Trees

Decision trees are another classification method that uses word features within a sequence to create a tree structure, with each node containing a decision rule determining whether the text belongs to a specific category.^[25,26]

Artificial Neural Networks (ANNs)

ANNs process word features within a sequence through a multi-layered network to determine whether a text belongs to a specific category.^[27]

For this study, Artificial Neural Networks (ANNs) were chosen for text classification due to their ability to learn from large datasets, which is ideal for solving complex problems such as text classification by providing sufficient data for better results. ANNs offer a flexible and customizable structure for learning relationships and patterns in texts, allowing for greater flexibility in analyzing features and achieving improved results in text classification.^[28] ANNs can also perform well when encountering new and different texts, utilizing pre-learned models for successful classification of previously unseen texts. Additionally, ANNs can learn semantic relationships and emotional tones, which are important for text classification.^[29]

In this study, a neural network was created using the *MLPClassifier* from the Python Scikit library, which is an open-source machine learning library written in Python that is frequently preferred for creating ANNs due to its ease of use. Scikit contains many predefined functions and classes necessary for creating ANN models and is a smaller, lighter library compared to larger-scale ANN libraries like *TensorFlow* and *PyTorch*, making it more suitable for smaller projects and faster prototyping.

Data Collection and Analysis Results

The Turkey National Thesis Center,^[30] administered by the Higher Education Council (YÖK) of Turkey, serves as a central repository for postgraduate theses completed in Turkish universities, making them accessible to researchers. The main purpose of this center is to facilitate researchers' access to academic resources and contribute to scholarly endeavors. The Thesis Center houses a comprehensive collection of theses across various disciplines, providing students, academics, and other researchers with a valuable source of information. Furthermore, the center supports the advancement of postgraduate education in Turkey and encourages the dissemination of academic knowledge. Figure 1 displays a sample search result page from the Turkey National Thesis Center website.

For the scope of this study, a total of 320 theses written between 2018 and 2023 were randomly selected from the Turkey National Thesis Center. Only English-language theses were chosen to be included in the sample. Table 1 illustrates the criteria we used for data selection. The theses were classified according to their scientific discipline, with the list of disciplines selected from SpringerLink.^[31] For classification, we utilized data from publications available on SpringerLink. Specifically, we focused on the titles and abstracts of the publications for the classification task.

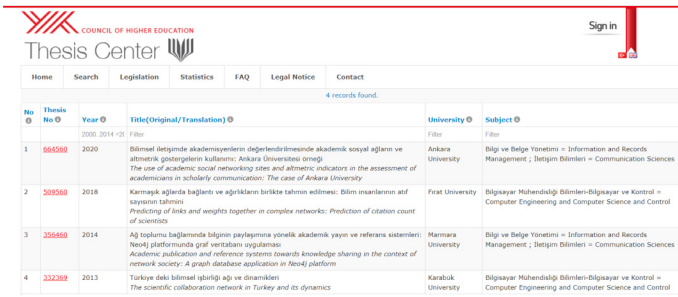
Table 1: Word Types and Numbers by Discipline.

Discipline	Noun	Verb	Adjective	Total W Number	Unique W Number	Word Richness
Architecture	24,498	4,145	3,989	579,185	26,962	0.0466
Biomedicine	30,085	2,583	3,673	456,737	31,498	0.0690
Business and Management	20,433	3,088	3,141	444,378	22,207	0.0500
Chemistry	18,784	2,581	3,254	414,607	20,655	0.0498
Computer Science	13,857	2,623	2,606	253,413	15,629	0.0617
Criminology and Criminal Justice	30,889	5,090	4,439	636,901	33,890	0.0532
Cultural and Media Studies	19,358	4,582	3,667	396,268	22,974	0.0580
Earth Sciences	13,927	2,459	2,683	297,206	15,402	0.0518
Economics	15,809	3,198	2,914	346,602	17,992	0.0519
Education	21,130	2,895	2,961	506,856	22,461	0.0443
Energy	21,569	3,938	3,637	514,555	23,601	0.0459
Engineering	19,776	2,004	2,338	367,636	20,373	0.0554
Environment	23,415	3,021	3,652	512,936	24,984	0.0487
Finance	18,946	3,192	2,823	410,562	20,189	0.0492
Geography	25,156	3,509	3,715	474,209	27,268	0.0575
History	70,103	5,110	4,847	2,727,715	69,727	0.0256
Law	26,332	5,322	4,324	658,072	29,417	0.0447
Life Sciences	25,619	1,808	2,640	383,625	25,911	0.0675
Linguistics	22,212	3,758	3,346	806,509	24,536	0.0304
Literature	28,552	5,238	4,724	543,334	32,733	0.0602
Materials Science	26,438	2,720	3,333	498,492	27,311	0.0548
Mathematics	9,324	1,359	1,294	293,081	10,266	0.0350
Medicine and Public Health	25,289	2,153	3,237	408,395	26,115	0.0639
Philosophy	31,938	4,776	4,822	728,695	35,713	0.0490
Physics	12,725	2,201	2,041	281,786	14,196	0.0504
Political Science	25,945	4,987	4,544	658,645	29,669	0.0450
Popular Science	23,672	3,653	3,705	465,393	25,465	0.0547
Psychology	32,445	2,898	3,907	615,173	33,422	0.0543
Religious Studies	50,216	3,574	4,234	1,093,825	50,570	0.0462
Social Sciences	24,868	4,774	4,407	618,703	28,099	0.0454
Statistics	11,077	2,161	1,978	248,033	12,375	0.0499

The Stanford NLP^[32] library provides a suite of tools consisting of pre-trained modules for performing Natural Language Processing (NLP) tasks. These modules facilitate various tasks such as tokenization, sentence segmentation, and Part-of-Speech (POS) tagging of a given text. Tokenization is the process of dividing a text into words or symbols. The Stanford NLP library accomplishes this task using a class called *TokenizerAnnotator*. This class takes a text input and returns a list of type `List<CoreLabel>`, where each element represents a word or symbol in the input text. Sentence segmentation involves identifying sentences within a text. The Stanford NLP library carries out this task using a class called

WordsToSentencesAnnotator. This class takes a tokenized text list as input and returns a list of type `List<CoreMap>`, where each element represents a sentence in the input text. POS tagging determines grammatical information for each word in a text. The Stanford NLP library performs this task using a class called *POSTaggerAnnotator*. This class takes a tokenized text list as input and returns a list of type `List<CoreMap>`, where each element represents a word in the input text along with its grammatical information.

Using the Stanford NLP library, the tokenization, sentence segmentation, and POS tagging processes were applied to the



No	Thesis No	Year	Title(Original/Translation)	University	Subject
1	664560	2020	Bilimsel iletişimde akademisyenlerin değerlendirilmesinde akademik sosyal ağların ve altmetrik göstergelerinin kullanımı: Ankara Üniversitesi örneği The use of academic social networking sites and altmetric indicators in the assessment of academicians in scholarly communication: The case of Ankara University	Ankara University	Bilgi ve Belge Yönetimi = Information and Records Management ; İletişim Bilimleri = Communication Sciences
2	509560	2018	Karmaşık ağlarda bağlantı ve ağırlıkları birlikte tahmin edilmesi: Bilim insanlarının ağıf sayısını tahmin etme Predicting of links and weights together in complex networks: Prediction of citation count of scientists	Fırat University	Bilgisayar Mühendisliği Bilimleri-Bilgisayar ve Kontrol = Computer Engineering and Computer Science and Control
3	356660	2014	Ağ yapısına bağlı olarak bilgi paylaşımına yönelik akademik yayın ve referans sistemleri: Bilgi paylaşımında graf veritabanı uygulamaları Academic publication and reference systems towards knowledge sharing in the context of network society: A graph database application in beed platform	Narmanç University	Bilgi ve Belge Yönetimi = Information and Records Management ; İletişim Bilimleri = Communication Sciences
4	332360	2013	Türkiye'deki bilimsel işbirliği ağı ve dinamikleri The scientific collaboration network in Turkey and its dynamics	Karabük University	Bilgisayar Mühendisliği Bilimleri-Bilgisayar ve Kontrol = Computer Engineering and Computer Science and Control

Figure 1: The Turkey National Thesis Center Search Screen.

specified text. Subsequently, each word in the text was processed to extract only certain word types, such as nouns, verbs, and adjectives. Words with fewer than two characters were excluded to avoid incorporating non-word values from formulas and tables into the calculation. Similarly, words containing characters outside the English character set were disregarded. This allowed for the computation of the number of unique words. Finally, word diversity was calculated by dividing the number of unique words by the total word count. During the selection of theses, a completely random function was employed, with the condition that no two theses from the same discipline, year, author, or institution were included. Only theses with full-text access available and published in last ten years were chosen for this study.

Table 2 contains data derived from the theses used in this study, with 10 theses selected from each discipline. The columns for Nouns, Verbs, and Adjectives represent the total count of each respective word type in the selected ten theses. The Unique W Number column displays the cumulative sum of distinct words found in the theses for each discipline. Word Richness, on the other hand, is the ratio of unique word count to the total word count.

Upon examining Table 2, it is evident that publications in the field of History utilize a significantly greater number of distinct nouns compared to other disciplines, followed by Religious Studies. Other disciplines display a similar usage of distinct nouns. The three disciplines with the lowest count of noun-type words are Mathematics, Statistics, and Physics. This data suggests that social sciences employ a more diverse set of nouns than natural sciences, possibly due to the broader range of area and descriptive information in social sciences. Regarding verb usage, Law exhibits the highest diversity, which may be attributed to the unique characteristics of legal studies. Mathematics, on the other hand, has the lowest verb diversity. In general, 8 of the top 10 disciplines with the highest verb diversity belong to social sciences, while the bottom 10 belong to natural sciences. When analyzing adjectives, there is no striking relationship between their usage and the disciplines. Although History, Philology, and Literature have higher adjective usage, and the bottom five are natural sciences, the difference is relatively small compared

to other word types. The total word number does not present a distinctive characteristic for the disciplines, despite the differences between the lowest and highest values. One crucial metric for determining word richness is the unique word count. Social sciences exhibit a clear dominance in this regard, with History, Religious Studies, and Philosophy taking the top three spots. Excluding Biomedicine at the seventh position, 10 out of the top 11 disciplines belong to social sciences. When comparing the average unique word count of the lowest three disciplines (Physics, Statistics, and Mathematics) with the top three, there is a more than three-fold difference. Word richness is defined as the ratio of unique word count to the total word count for each category. The top three highest word richness values belong to health sciences, which may be attributed to the discipline's unique and Latin-based vocabulary. There is no significant difference in word richness between social and natural sciences disciplines.

Normalization is a process used to eliminate scale differences between various features of a dataset. Min-Max normalization is a technique that transforms the values of a feature in a dataset to a specific range by rescaling the feature values between the minimum and maximum values.^[33] As a result, the feature values range between 0 and 1. In this study, Min-Max normalization was applied to the total word count and then subtracted from 1. This was done to ensure that a higher total word count negatively impacts the result.

The Min-Max normalization function was executed with the lowest total word count set to 0 and the highest total word count set to 5 million. After this step, the normalization coefficient was recorded in a new column by applying normalization to all disciplines as mentioned above, subtracting the result from 1, and then multiplying the unique word count. The product of this calculation was then multiplied by the word richness value and by 100 to obtain the normalized word richness value. Multiplying by 100 was done to enhance the readability of the Table 2.

The normalization of the unique count resulted in minor position changes in the table, but no significant alterations were observed. There were more changes in the normalized word richness values, but again, not significant enough to alter the previous findings. Although there were changes within the top 10 and bottom 10, no external changes were observed. Table 3 contains two abbreviations: UWNAN (Unique Word Number After Normalization) and WRNAN (Word Richness Number After Normalization). In Equation 1, the normalization function used in the application is presented.

$$f_{\text{Normalization}}(x) = 1 - (x - \text{Min}(X^{\text{ALL}})) / (\text{Max}(X^{\text{ALL}}) - \text{Min}(X^{\text{ALL}})) \quad (1)$$

Figure 2 shares the same content as Table 2. In Figure 2, the exceptional case in history is more clearly visible. Additionally, it can be observed that the word richness in social sciences is

Table 2: Word Types After Normalization.

Discipline	Total Word Number	Unique Word Number	Word Richness	Normalization	UWNAN	WRNAN X 100
Biomedicine	456,737	31,498	0.069	0.909	28,621	6.27
Life Sciences	383,625	25,911	0.068	0.923	23,923	6.23
Medicine and Public Health	408,395	26,115	0.064	0.918	23,982	5.87
Computer Science	253,413	15,629	0.062	0.949	14,837	5.86
Literature	543,334	32,733	0.060	0.891	29,176	5.37
Cultural and Media Studies	396,268	22,974	0.058	0.921	21,153	5.34
Geography	474,209	27,268	0.058	0.905	24,682	5.20
Engineering	367,636	20,373	0.055	0.926	18,875	5.13
Popular Science	465,393	25,465	0.055	0.907	23,095	4.96
Materials Science	498,492	27,311	0.055	0.900	24,588	4.93
Earth Sciences	297,206	15,402	0.052	0.941	14,486	4.87
Economics	346,602	17,992	0.052	0.931	16,745	4.83
Psychology	615,173	33,422	0.054	0.877	29,310	4.76
Physics	281,786	14,196	0.050	0.944	13,396	4.76
Statistics	248,033	12,375	0.050	0.950	11,761	4.74
Criminology and Criminal Justice	636,901	33,890	0.053	0.873	29,573	4.64
Chemistry	414,607	20,655	0.050	0.917	18,942	4.57
Business and Management	444,378	22,207	0.050	0.911	20,233	4.56
Finance	410,562	20,189	0.049	0.918	18,531	4.52
Environment	512,936	24,984	0.049	0.897	22,421	4.37
Philosophy	728,695	35,713	0.049	0.854	30,508	4.19
Architecture	579,185	26,962	0.047	0.884	23,839	4.12
Energy	514,555	23,601	0.046	0.897	21,172	4.12
Education	506,856	22,461	0.044	0.899	20,184	3.98
Social Sciences	618,703	28,099	0.045	0.876	24,622	3.98
Political Science	658,645	29,669	0.045	0.868	25,761	3.91
Law	658,072	29,417	0.045	0.868	25,545	3.88
Religious Studies	1,093,825	50,570	0.046	0.781	39,507	3.61
Mathematics	293,081	10,266	0.035	0.941	9,664	3.29
Linguistics	806,509	24,536	0.030	0.839	20,578	2.55
History	2,727,715	69,727	0.026	0.454	31,688	1.16

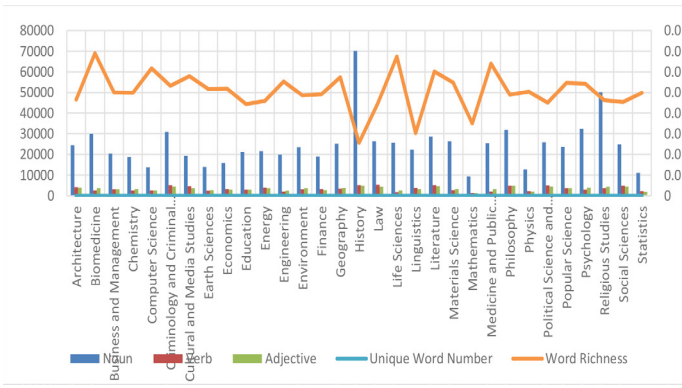


Figure 2: Word Types Statistics by Disciplines.



Figure 3: Word cloud by common usage of the most frequently used verbs in data.

Appendix 1: List of the Most Common Verbs by Discipline.

Discipline	Verbs
Architecture	are, was, have, has, were, been, used, built, based, including
Biomedicine	are, was, were, used, have, interfaces, using, treated, compared, has
Business and Management	are, has, have, used, was, pairing, been, given, were, defined
Chemistry	was, were, are, used, have, using, based, spouted, has, dried
Computer Science	are, used, based, using, have, has, were, was, use, given
Criminology and Criminal Justice	was, were, are, have, has, been, had, based, did, given
Cultural and Media Studies	are, was, were, has, have, used, been, had, being, based
Earth Sciences	are, used, using, was, were, have, has, reinforced, obtained, based
Economics	are, have, was, has, were, used, been, accessed, does, according
Education	was, were, are, have, learning, used, based, found, had, related
Energy	are, was, have, has, been, used, were, based, making, given
Engineering	are, was, used, using, were, obtained, given, has, have, seen
Environment	are, was, were, used, using, have, given, based, has, obtained
Finance	are, have, was, has, used, been, were, based, using, made
Geography	are, was, were, used, had, have, based, has, defined, using
History	was, were, used, have, had, let, shown, ran, follows, obtain
Law	are, was, has, have, were, been, had, made, based, related
Life Sciences	was, were, are, used, has, have, using, produced, found, had
Linguistics	are, was, were, have, used, has, use, using, been, make
Literature	are, was, were, have, has, had, been, being, used, according
Materials Science	was, are, were, used, have, shown, using, coated, has, given
Mathematics	are, have, let, following, has, given, defined, follows, called, obtain
Medicine and Public Health	are, were, was, based, used, included, have, has, observed, been
Philosophy	are, has, have, stolen, was, were, being, does, been, based
Physics	are, used, using, have, has, shown, given, based, called, was
Political Science	was, are, were, has, have, had, been, generalized, stated, based
Popular Science	are, was, were, have, used, automated, writing, using, has, given
Psychology	are, were, was, have, has, related, had, used, found, been
Religious Studies	are, was, were, have, used, has, had, been, being, given
Social Sciences	are, was, were, have, has, been, being, had, used, according
Statistics	are, used, have, using, has, was, set, based, were, given

Appendix 2: List of the Most Common Adjectives by Discipline.

Discipline	Adjectives
Architecture	nthe, social, economic, urban, different, other, new, political, local, such
Biomedicine	different, nthe, epileptic, other, high, human, small, first
Business and Management	nTable, nthe, nAnnual, other, Much, online, new, such, nImportant, different
Chemistry	different, high, nthe, magnetic, such, other, higher, molecular, ionic, low
Computer Science	nthe, different, such, other, human, new, secret, first, same, high
Criminology and Criminal Justice	other, nthe, international, Turkish, new, such, political, cyber, important, different
Cultural and Media Studies	nthe, other, different, urban, such, political, Iranian, new, first, same
Earth Sciences	nthe, different, lower, other, natural, such, nTable, seismic, concrete, upper
Economics	other, economic, nthe, such, general, social, new, important, more, different
Education	high, other, nthe, significant, olan, experimental, emotional, different, such, conceptual
Energy	nuclear, nthe, other, different, public, such, high, solar, political, personal
Engineering	nthe, different, other, nTable, optimal, total, triangular, olan, circular, digital
Environment	different, nthe, high, low, nTable, organic, other, higher, such, ferric
Finance	free, other, financial, nthe, finansal, foreign, first, different, new, important
Geography	nthe, other, local, new, different, high, black, such, first, nTable
Law	nthe, other, political, such, social, first, international, human, new, Turkish
Life Sciences	different, nTable, high, green, olan, other, low, nthe, significant, such
Linguistics	nthe, audio, other, different, such, Turkish, more, first, positive, same
Literature	other, nthe, qualitative, social, different, such, many, new, important, first
Materials Science	nthe, different, high, blank, other, such, composite, low, deep, adhesive
Mathematics	such, real, nthe, compact, continuous, linear, other, positive, dimensional, finite
Medicine and Public Health	adrenal, different, primary, other, healthy, nTable, nthe, human, Adrenal
Philosophy	nthe, other, ethical, olan, such, true, same, cognitive, different, first
Physics	nthe, other, high, different, same, random, nThe, hetero, single, such
Political Science	political, nthe, other, social, Kurdish, such, civil, economic, Turkish, important
Popular Science	nthe, other, different, human, local, nTable, high, free, such, same
Psychology	sexual, nthe, other, high, human, physical, significant, affective, nThe, different
Religious Studies	olan, inde, nthe, other, onun, Islamic, such, Malaysian, thermal
Social Sciences	nthe, other, such, social, public, new, economic, different, important, first
Statistics	nthe, nTable, different, other, same, such, new, physical, first, independent

History is not on this list. The adjective used in History and used more than others at a distinctive rate could not be found.

differences in language use across various academic disciplines and contexts.

This study represents a significant step in analyzing lexical richness in academic texts across specific disciplines. However, certain limitations are present, which must be considered when interpreting and generalizing the findings.

Primarily, the inclusion of only ten theses from each discipline restricts the generalizability of the results. Theses often represent the most profound part of research, therefore, there can be substantial stylistic and lexical variations among them. Consequently, a larger sample size could potentially yield more

reliable and generalizable results. The fact that these were sourced from a single country's thesis center also confines the generalizability of the outcomes. This is particularly true given that the center is located in a non-native English-speaking country. What different countries and linguistic backgrounds influence students' academic writing styles and vocabularies is largely unknown, and this study presumes the universality and standardization of language.

These limitations underscore the need for a cautious interpretation of this study's findings. However, even with these constraints, the study provides valuable insights into how vocabulary and lexical richness vary across different academic disciplines. This research

could form the foundation for future studies in this area, and larger sample sizes, theses from diverse geographical locations, and a more detailed evaluation of the classification algorithm could enhance the strength and generalizability of such studies.

CONCLUSION

In conclusion, this study investigated the lexical richness in English-language theses across a wide range of academic disciplines. The analysis revealed that social sciences tend to exhibit greater lexical richness compared to natural sciences, with disciplines like History, Religious Studies, and Philosophy demonstrating higher unique word counts. The findings also highlighted that verb diversity is generally higher in social sciences, while noun diversity presents more variation across disciplines. The application of normalization to the unique word count and word richness values led to minor changes in the rankings but did not significantly alter the overall conclusions. The word clouds generated from the most frequently used verbs and nouns in the dataset provided further insights into the similarities and differences in word usage across disciplines.

Several limitations of this study should be noted, including the relatively small sample size of ten theses per discipline and the selection of theses from a single thesis center in a non-English-speaking country. Future research could address these limitations by increasing the sample size, incorporating theses from multiple centers and countries, and comparing the results between native and non-native English-speaking contexts. Moreover, advanced NLP methods and deep learning techniques could be employed in future research to analyze the contextual meaning of words, further enhancing the evaluation of lexical richness in academic texts.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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