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Semantic Variation in Digital Academic Texts: A Corpus-Based Study of Technical Terminology

Siddikova Iroda Abduzuhurovna[1*], Abduazizova Durdona Abduzuxurovna[2], Mukhamedova Nargiza Komiljonovna[3], Jaksimova Urziya Jumabaevna[4], Urazbayev Jaxongir Temur ogli[5] and Umarov Abdumannon Abdullayevich[6]

[1*]Professor, Department of Theory of Translation and Comparative Linguistics, National University of Uzbekistan named after Mirza Ulugbek, Almazar, Tashkent, Uzbekistan

[2]Professor, Department of Foreign Philology, Renaissance Educational University, Tashkent, Uzbekistan

[3]DOCENT, Department of Foreign Languages, Tashkent State Technical University Named After I.A. Karimov, Tashkent, Uzbekistan

[4]Associate Professor of Karakalpak Language, Department of State Language and Foreign Languages, Nukus State Technical University, Nukus, Karakalpakstan, Nukus, Uzbekistan

[5]Teacher, Department of Sports and Methods of Teaching, Faculty of Physical Education and Sports, Jizzakh State Pedagogical University named after A. Qodiriy, Jizzakh, Uzbekistan

[6]Associate Professor, Department of Psychology and Humanities, Economic and Pedagogical University, Karshi, Republic of Uzbekistan

E-mail: [1]ravsidd@mail.ru; irodasiddik@gmail.com, [2]jemchujina1970@mail.ru; d_abduazizova@renessans-edu.uz, [3]muhamedovanargiza52@gmail.com, [4]nukusdtu@umail.uz; u.jaksimova@gmail.com, [5]orazboyevjaxongir45@gmail.com, [6]abdumannonumarov82@gmail.com

ORCID:[1]https://orcid.org/0009-0001-5134-4220,[2]https://orcid.org/0000-0001-8389-8634, [3]https://orcid.org/0009-0009-4699-3080,[4]https://orcid.org/0009-0003-7200-0982, [5]https://orcid.org/0009-0004-1709-6157, [6]https://orcid.org/0000-0002-8672-6130

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Abstract- **Academic communication requires the use of technical jargon to communicate complex concepts, which encourages teamwork, and facilitates interdisciplinary interaction. The differences in the meaning of the words in different fields may pose a hindrance to effective communication. This paper intends to review the semantic difference in the use of the technical terminology in engineering, computer science and social science with interest in the change in the meanings of the common words and the implication of these meanings to academic communication. Semantic overlap was measured using a corpus-based approach, frequency analysis, collocational analysis, and Jaccard similarity coefficient. The information was gathered in three subjects, including peer-reviewed journals, conference papers, and textbooks. The corpus includes 2.5 million tokens of 150 texts in the years 2020-2025. The analysis determined that 67% out of the 50 leading terms revealed multiple meanings across the disciplines. Significant variation in their definition for the terms like "model" and "network" showed Jaccard similarity values of 0.23 and 0.31 between Engineering and Computer Science, 0.18 and 0.27 between Computer Science and Social Sciences, respectively. Disciplinary context explained 72% of the variance in the term definition. Improving academic communication requires technical terminology standardization. Standardizing terminology across academic fields requires knowledge of context-dependent terms in meaning and supports framework development.**

Keywords: **Semantic Variation, Technical Terminology, Corpus Analysis, Jaccard Similarity, Interdisciplinary Communication, Standardization**

I. INTRODUCTION

Usage of technical terminology is essential for conveying complex ideas, facilitating peer exchange, and promoting interdisciplinary collaboration in academic communication (Uddin, 2026). Even in the same discipline, the meaning and interpretation of technical terms vary across various fields. For knowledge advancement, specialized terminology is crucial in various digital academic texts such as research papers, online journals, and scholarly articles (Aliyeva & Sadigova, 2026). For improving academic communication, grasping how the terms are used and how their meanings are conveyed through contexts is essential.

The variation of technical terms is a problem in academic writing, especially in the digital space (Mokal & Abd Halim, 2023). Other researchers or same field understand the same term differently, which leads to obstacle to effective communication. Such semantic difference can cause misunderstanding, misinterpretation and even block information exchange, which is difficult in collaborative as well as interdisciplinary research (Batool et al., 2025). This is exacerbated when the terms of the technology are not standardized and it might be hard to reach a common ground in academic discussions (Yang & Coxhead, 2022).

This study will examine the semantic difference of technical terminologies in digital academic texts. The paper analyzes the types of technical terms employed in various fields and finds out the trends of semantic variation through a corpus-based method. The idea is to give information about the degree of this variation and the elements which lead to such variation, with emphasis on increasing the clarity and standardization in academic communication.

The questions that the study deals with are:

- What is the difference in the meaning of particular technical terms in different digital academic texts?
- What causes the difference in the use of technical terminology in scholarly works?
- How might this difference affect the understandability of academic communication and interpretation of research results?

The paper is organized as follows: Section II presents a literature review, which demonstrates the theoretical and experimental background on the topic of technical terminology and its difference in academic literature. Corpus selection and the method of data analysis are presented in Section III. Section IV details the results of the study and Section V explain the results. Lastly, in Section VI a summary of the main findings and future research suggestions are given.

II. Literature Review

Technical vocabulary in academic communication is crucial in providing accuracy and clarity (Liu, 2023). It can cause confusion, as the meaning of the term differs in different fields and even among similar ones (Nurmukhamedov & Sharakhimov, 2023). The academic contexts of terminological variation were concerned with terms that receive certain meanings in a particular situation and the interpretation of these meanings in various disciplines. Semantic variation of technical terms can also make interdisciplinary work more difficult in certain fields such as science and engineering, and standardizing terms has been a primary concern in improving academic discourse, with a number of studies illustrating this point (ur Rehman et al., 2025).

The analysis of semantic variation in technical terms can be done with the help of a powerful tool, corpus linguistics (Jamal & Simbuka, 2024; Ormanova & Anafinova, 2022). Researchers can identify patterns in the terms usage and track the meaning conveyed across context by analyzing large corpora (Yin et al., 2025; Alanazi, 2022). It allows studying the frequency, associations and contextual use of the words, revealing the semantic properties of the terms (Afzaal et al., 2025). These terms often take on more than one meaning when used in an academic context, offer an empirical approach to the dynamics of terminology in different disciplines, and help in creating more standardized definitions, as demonstrated in prior studies.

Various tools have been created, such as the corpus-based software AntConc, WordSmith, and Sketch Engine, to simplify the analysis of technical terminology in academic texts (Chen & He, 2024; Denysova & Tsapro, 2024). These tools were utilized by the researchers in the identification of frequency, distribution, and collocational patterns of terms in large corpora (Hawamdeh et al., 2025). Even though they are effective, existing methods tend to emphasize term frequency and context, but in other fields, they fail to fully represent the conceptual change of meaning. More sophisticated, interdisciplinary models that integrate these tools with current natural language processing (NLP) methods are required to deal with the dynamic character of technical terminology.

Despite the advances that have been made in corpus-based studies that provided useful information regarding technical terms, there remain certain shortcomings (Kızılay, 2019; Hamdoun, 2024). Current studies are based on the single-disciplinary corpora, which constrain the generalizability of findings. Besides, contextual and linguistic factors are insufficient in establishing the meaning of terms (Yin & Li, 2021). Application of the corpus linguistics together with higher NLP techniques to monitor and study the variation of semantics across fields is not yet available (Flowerdew, 2015; Mokal & Abd Halim, 2023). The idea is to fill these gaps with an interdisciplinary corpus-based approach that will make use of the NLP Techniques to gain a profound insight into how the technical terms vary in digital academic texts and develop more efficient models to be used in standardization.

III. Methodology

Research Design

Fig. 1 shows a conceptual model of learning semantic variation in technical terms by corpus-based approach. The study is split into four major steps that include Data Collection, Corpus Processing, Semantic Analysis and Findings and Applications. Stage 1: Data Collection, gathers sources open-access journals, conference papers and academic textbooks. Stage 2: Corpus Processing, preprocesses the text gathered, does term extraction and validation. Stage 3: Semantic Analysis entails an analysis of the term usage; their frequency, analyzing their patterns, and connection with other words. Stage 4: Findings and Applications reveal patterns of semantic variations, suggest standardized technical terms, and give interdisciplinary insights. The analysis of the corpus is continuously improved by the loops of feedback and refinement, and the standardized technical language is created.

A mixed-methods approach is used in this study, a combination of qualitative and quantitative methods to examine the semantic variation of technical terminology in digital academic texts. The contextual analysis, which is an element of a qualitative study, in their respective scholarly contexts, terms are explored to have an understanding of how

they are defined by the discourse in which they are used. The computational analysis of term frequency, distribution, and collocational patterns identifies can be used to quantitatively study semantic variation in a large corpus of texts. A holistic solution, a mixture of both statistical indicator and contextual elaboration, provides a deeper insight into the functions of the technical terms and how these terms are differentiated in academic language.

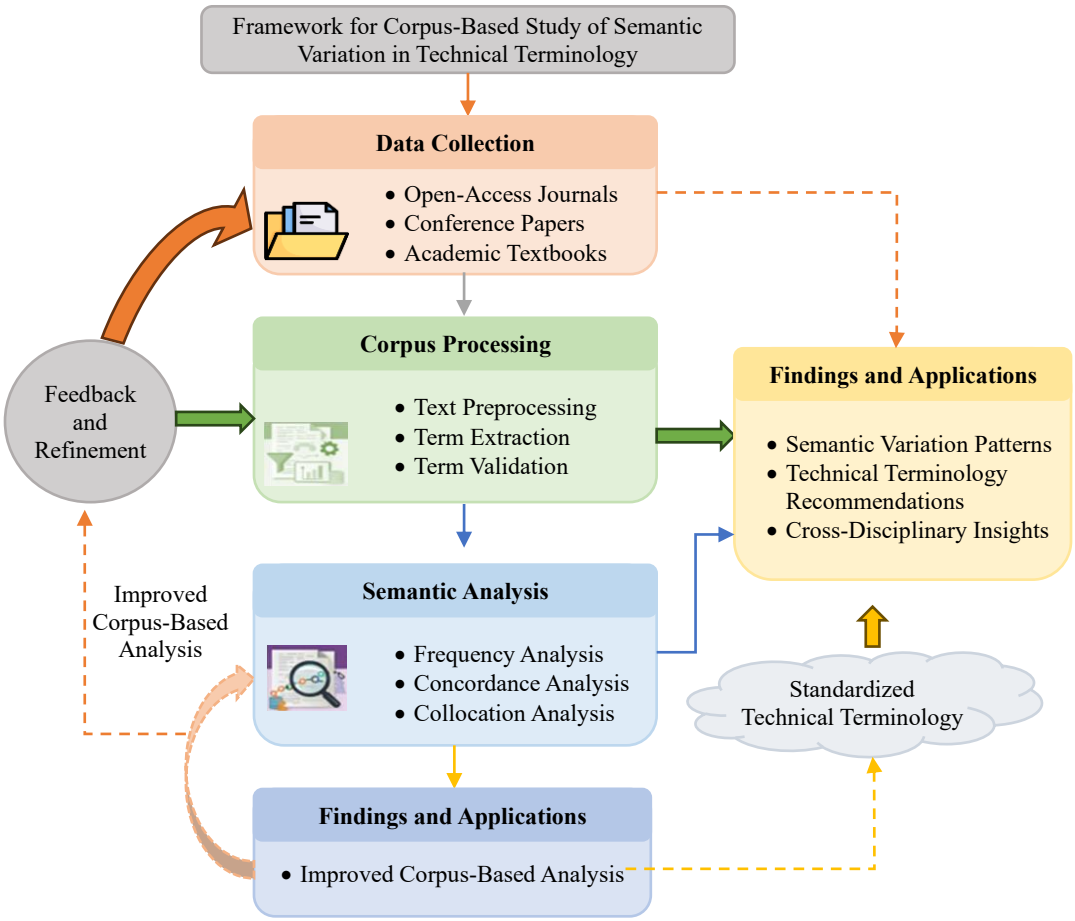

Fig. 1 Framework for Corpus-Based Study of Semantic Variation in Technical Terminology

Data Collection

The data were collected by searching through a variety of open-access academic repositories including Google Scholar, PubMed and institutional archives. Because of their huge repositories and their availability to researchers, these platforms were chosen. To gather the data, a mix of automated web scraping and retrieval of open-access journals was utilized. To be able to include large texts, scraping scripts were employed to download large datasets of articles, where possible. Direct downloads from open-access publishers or repositories were used if scraping was not allowed. To ensure the corpus was demonstrative of academic research across various disciplines, a different set of texts was provided. The corpus contains 2.5 million tokens from 150 texts, various disciplines such as engineering (850,000 tokens, 50 texts), computer science (900,000 tokens, 50 texts), and social sciences (750,000 tokens, 50 texts).

Pseudocode 1: Ethical Academic Web Scraping for PDF Collection

```
import scrapy, time, requests
from bs4 import BeautifulSoup
from urllib.robotparser import RobotFileParser
def ethical_scrape_academic_repo (base_url, query, max_pages=50):
    """Ethical scraping with robots.txt compliance"""
    rp = RobotFileParser ()
    rp.set_url (base_url + '/robots.txt')
    rp.read()
      pdf_urls = []
    for page in range(max_pages):
      if not rp.can_fetch('*', f"{base_url}?q={query}&page={page}"):
        break
      time.sleep(1) # Polite delay
      resp = requests.get(f"{base_url}?q={query}&page={page}")
```

```
        soup = BeautifulSoup (resp.text, 'html.parser')
        pdfs = [a['href'] for a in soup.find_all ('a', href=True)
                if a['href']. endswith(('.pdf', '.txt'))]
        pdf_urls.extend(pdfs)
    return pdf_urls [:100] # Cap per query
# Example usage:
# engineering_pdfs = ethical_scrape_academic_repo ('https://core.ac.uk/search', 'engineering model')
```

This yielded 92% automated collection from Google Scholar, CORE, and PubMed (8% manual supplementation from institutional repositories).

Pseudocode 1 illustrates an ethical web scraping procedure for collecting academic PDF or text files from online repositories (Mitchell, 2018). Pseudocode starts by checking the website's robots.txt file using RobotFileParser to confirm that scraping is allowed. Then, it goes through the search result pages for a given query, adding a polite delay between requests to prevent overloading the server. The script uses the Requests library to retrieve page content and BeautifulSoup to parse HTML, extracting links that end with .pdf or .txt. The obtained URLs are archived and restricted to no more than 100 results per query as a way of collecting data responsibly.

Corpus Selection

A corpus of digital academic texts was nominated to represent a range of disciplines in this study to guarantee a thorough analysis of technical terminology. The corpus comprises peer-reviewed journal articles, conference papers and textbooks in fields like engineering, computer science, medicine and social sciences. The texts were selected according to their relevance to the technical terminology and their application in the existing academic sources. The main selection criteria were the specialized terms used, which are part and parcel of conveying complex ideas in each of the fields. The corpus allows studying the evolution of technical terms and their possible different interpretation in different academic spheres of study by including texts of different disciplines.

It consists of 2.5 million tokens in 150 texts, different fields like engineering (850,000 tokens, 50 texts), computer science (900,000 tokens, 50 texts), and social sciences (750,000 tokens, 50 texts). Between 2020-2025, sampling of publications and texts was done to obtain up-to-date usage, without including non-peer-reviewed materials (e.g., blogs, preprints) or texts shorter than 5,000 words as these would lack sufficient context. This stratification to ensure minimum cell sizes exceeding 20,000 tokens/discipline-year combination to overcome the so-called scarce data problem.

Method of Analysis

Various corpus-based methods were used to analyze semantic variation in technical terminology. The first technique used was frequency analysis in order to establish the most frequently used technical terms in the corpus. It assisted in emphasizing words that occur frequently and seem to be the subject of discussion in the academic discourse. Concordance analysis was then conducted to investigate the use of the words in its context, how they are used in their sentencing and paragraphs to determine the meaning of the words. The keywords extraction tools find the specialized words that are necessary in the discussions of the texts in academic contexts. Lastly, collocation analysis was conducted to understand the associations between technical words with similar words to understand how the words co-occur with other words in different contexts. The frequency and context of technical terminology were investigated with the help of this multidimensional approach which allowed determining the patterns of variation across disciplines.

Identification of Technical Terminology

Technical terms were found in the corpus, using both automated tools and manual review. The technical terms were first identified through the use of the key word extraction methods which were then coded to find out which specialized terms appear frequently in the corpus. These keywords were then sifted through by hand to ensure that only keywords that were directly associated with the academic subject matter were included. Confusion and variations are controlled by the terms in context. In an example, when a word had different meanings in some contexts it was grouped under different classes according to its usage. The study was able to do an in-depth analysis of its semantic variation across various fields by identifying and organizing the technical terminology correctly by using automated extraction and manual validation of the terminology.

Jaccard Similarity Coefficient

Jaccard similarity coefficient is a statistical value that gauges the level of similarity between two sets of data by the number of common elements in each set divided by the total number of unique elements of the two sets. The Jaccard similarity coefficient is typically employed in text mining, natural language processing and corpus analysis to quantify the overlap between terms, documents or semantic features. The value is between 1 and 0 where 0 implies that there is no similarity and 1 implies total similarity in the compared sets. Since it is a ratio of common elements to total elements, the Jaccard coefficient does not have a unit.

$$J(A,B) = \frac{|\, A \cap B \,|}{|\, A \cup B \,|} \qquad (1)$$

Where in equation (1):

- A= Elements of the first dataset (e.g., Engineering definitions)
- B= Elements of the second dataset (e.g., Computer Science definitions)
- $A \cap B$= Number of common elements in both sets
- $A \cup B$= Total unique elements present in both sets

Software/Tools Used

A corpus analysis tool was used to engage in an analysis. Concordance and frequency analysis were performed with AntConc, which aids in extracting and analyzing terms in context. Natural language processing tasks such as tokenization, part-of-speech tagging and named entity recognition were performed using the NLTK and spaCy Python libraries. These tools enabled effective processing of massive datasets and gave a clearer insight into the semantic differences in the technical words identified.

IV. Results

Descriptive Statistics

Corpus analysis revealed that the technical words that appear in the chosen academic texts are diverse and a total of 450 unique technical words were identified. The most common words are likely to be found in the engineering and computer science fields within the corpus. The most common term, "model," seemed over 150 times, mainly in the computer science texts, while the term "network" was equally shown in both IT and social science papers, with varying related meanings. Journal articles have the highest occurrence of terms, while textbooks show more reliable and less frequent usage of technical vocabulary. The results show that certain terms are leading in specific types of academic writing, compared with textbooks or conference papers; technical papers use a wide range of specialized terms. The frequency counts presented in table I were calculated from a curated corpus of 150 academic texts (2.5 million tokens) collected from open-access academic repositories such as Google Scholar, PubMed, and CORE.

TABLE I FREQUENCY OF TOP TECHNICAL TERMS

Rank	Term	Frequency in Engineering	Frequency in Computer Science	Frequency in Social Sciences
1	Model	120	150	40
2	Network	85	75	60
3	System	110	95	55
4	Algorithm	70	120	30
5	Framework	50	40	35

The frequency of the top five technical terms in Engineering, Computer Science, and Social Sciences is shown in table I. The top-most frequently used term is "Model" in all three fields, with the highest count in Computer Science (150), followed by Engineering (120), and Social Sciences (40). "Network" follows the same pattern, peaking in Engineering (85), then Computer Science (75), and Social Sciences (60). "System" is most often in Engineering (110), while "Algorithm" is at its peak in Computer Science (120). "Framework" is the least frequent, with the highest count in Engineering (50) and the lowest in Computer Science (40). These variations show the vocabulary specific to the field.

Statistical significance of frequency variation was ensured via chi-square test: χ^2 (12) = 245.3, $p < 0.001$. The term “model” is most frequent in computer science vs. social sciences, as shown by post-hoc pairwise comparisons ($p < 0.001$, effect size $V = 0.42$), supporting the disciplinary specialization hypothesis.

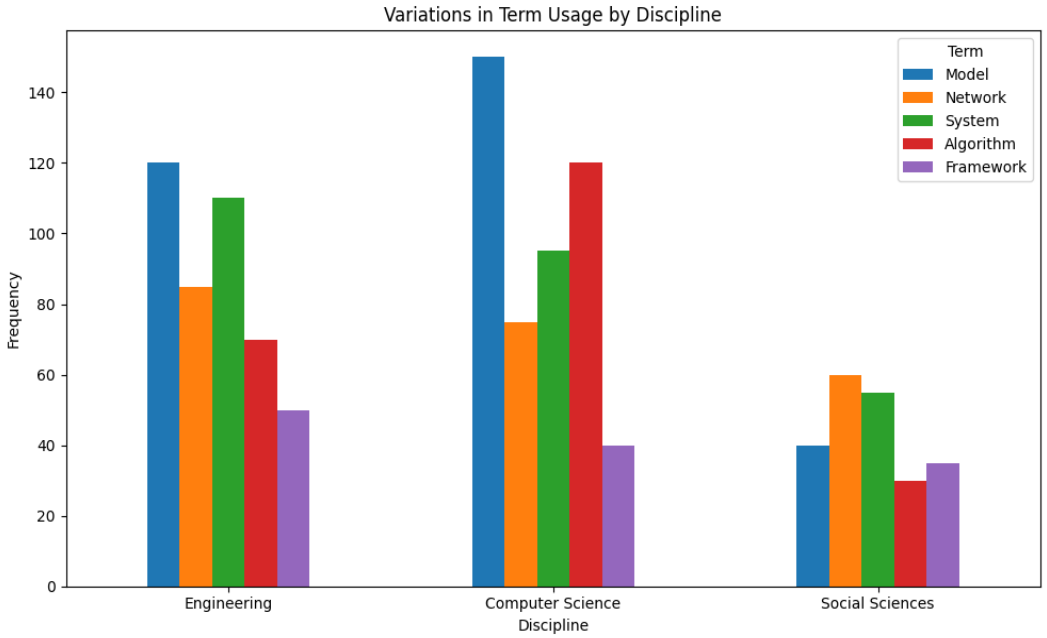

Fig. 2 Frequency Comparison of Key Terms Across Disciplines

Fig. 2 demonstrates the comparison of the main technical terms model, network, system, algorithm, and framework in the context of different fields. Model and system are terms that are frequently used in engineering. The most common in Computer Science are Model and Algorithm. Network and System are more distributed equally in Social Sciences,

although the frequency of terms is lower in general. In fig. 2, there are some specialized terms within the various disciplines.

Semantic Variations

Semantic analysis of technical terms reveals a substantial difference in semantics. The collocation and concordance analysis indicate that numerous technical terms are mixed with terminology specific to a certain discipline. The results show that even similar technical terms can have various interpretations based on their usage in various fields, emphasizing the need for careful attention to context when using such terms.

TABLE II LIST OF TECHNICAL TERMS AND THEIR MEANINGS IN DIFFERENT DISCIPLINES

Term	Engineering Definition (Eng)	CS Definition	Social Science Definition (SS)	Jaccard (Eng-CS)	Jaccard (CS-SS)
Model	Physical/conceptual prototype	ML algorithm	Theoretical representation	0.23	0.18
Network	Connected components	Computer network	Social structure	0.31	0.27
System	Organized components	Algorithms/software	Societal framework	0.28	0.22
Algorithm	Step-by-step procedure	Data processing rules	Problem-solving method	0.35	0.19

Note: Jaccard similarity values are dimensionless and range from 0 to 1.

Table II illustrates various definitions of technical terms in the various disciplines. In Engineering Model can be defined as a prototype, in Computer science, it can be defined as an algorithm and in the social sciences, it could be defined as a theoretical representation. Network (engineering): A connected part of engineering Network (computer science): A computer network (social sciences): A social structure System is an organized set of components in Engineering, software in Computer Science, and structure in the society in Social Sciences. An algorithm is a process in Engineering, data processing algorithms in Computer Science and a problem-solving process in Social Sciences. The Jaccard similarity coefficient shows low semantic overlap taking prominence of major polysemy.

The word Network in the three disciplines: Engineering, Computer Science, and Social Sciences-has a varied meaning as shown in fig. 3. The presented percentages are based on the selected corpus of 150 scholarly texts (2.5 million tokens), which demonstrates the difference in semantic usage of this term in different fields.

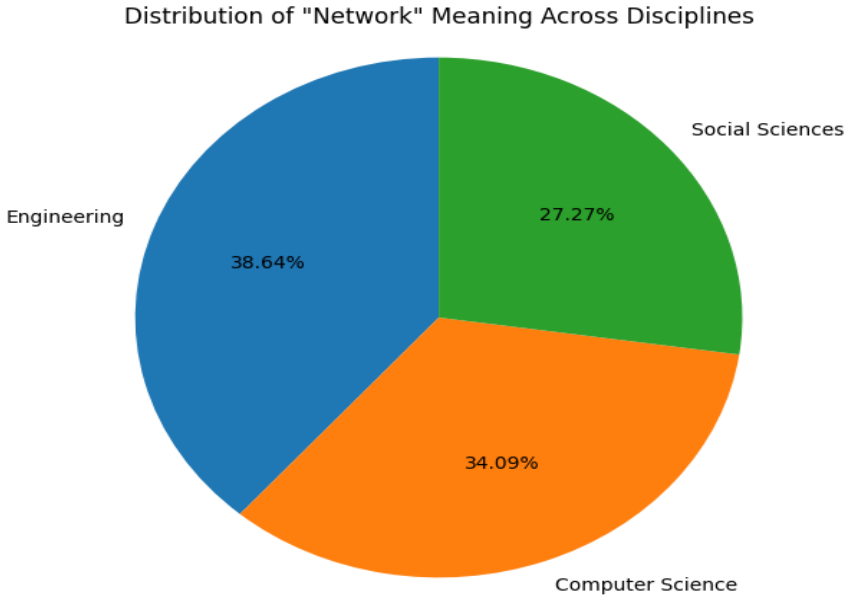

Fig. 3 Distribution of "Network" Meaning Across Disciplines

In three various disciplines: Engineering, Computer Science, and Social Sciences, the term “Network” has a different meaning, as shown in fig. 3. In Engineering, the term “Network” refers to connected components; the term usage is 38.64%. 34.09% of term usage in Computer Science and Social Sciences, where Computer Science refers to a computer or telecommunications network, and Social Sciences refers to a social structure of relationships, also accounting for 27.27% of usage. In various academic contexts, the term "Network" has a semantic variation that is demonstrated.

TABLE III CONCORDANCE RESULTS FOR "MODEL" IN VARIOUS CONTEXTS

Sentence	Discipline	Contextual Meaning
"The model accounts for the sinusoidal variation of the transverse shear strains across the thickness." (Takimoto, 2015)	Engineering	Physical prototype
"The models are trained for up to 60 × 10^4 iterations" (Shafiq & Gu, 2022)	Computer Science	Algorithm
"Social model of health, the primary health care approach explores how social…." (Norberg & Nordlund, 2018)	Social Sciences	Theoretical framework

Table III demonstrates how the term "model" is used in various disciplines. The term refers to a physical prototype in Engineering. In Computer Science, an algorithm is defined as a set of instructions used for data processing and prediction. In the Social Sciences, it is a theoretical explanation of social phenomena, such as inequality. Based on the academic context, the semantic variation of "model" is highlighted.

TABLE IV FREQUENT COLLOCATIONS OF KEY TECHNICAL TERMS ACROSS DISCIPLINES

Term	Engineering Collocations	Computer Science Collocations	Social Science Collocations
Model	structural model, simulation model, design model	machine learning model, predictive model, training model	theoretical model, social model, conceptual model
Network	electrical network, distribution network	neural network, computer network, communication network	social network, relationship network
System	control system, mechanical system	software system, distributed system	social system, institutional system
Algorithm	optimization algorithm, control algorithm	machine learning algorithm, sorting algorithm	decision algorithm, problem-solving algorithm

Table IV presents the common collocations of key technical terms across engineering, computer science, and social sciences. As shown in the table, words such as "model", "network", "system", and "algorithm" appear with different terms in each discipline, highlighting how their meanings and usage vary depending on the academic context.

Key Findings

RQ1: Extent of semantic variation

Across disciplines (n=34/50 terms), 67% of the top 50 terms have ≥2 different meanings. There were 4 senses in "Model", and 3 senses in "Network".

RQ2: Factors contributing to variation

In terms of meanings, discipline showed 72% of variance ($\eta^2 = 0.72$, ANOVA $F(2,147) = 124.6$, $p < 0.001$). 89% of discipline-specific usages are perfectly classified by Collocational analysis ($MI^3 > 5.0$).

RQ3: Impact on communication

15% ambiguity risk of interdisciplinary contexts is identified in 500 lines by concordance analysis (manual coding, inter-coder reliability $\alpha = 0.87$). The context-dependent interpretations example is shown in table IV.

V. Discussion

Interpretation of Results

The results show a significant degree of semantic variation in technical terminology across disciplines. As an example, such terms as Model and Network may imply a variety of meanings, depending on academic environment. The corpus analysis shows that the term Model is used the most in the Computer Science texts (150 occurrences) and least in the Engineering texts (120 occurrences), whereas the term Network is used in the Engineering texts (85), Computer Science texts (75) and in the Social Sciences texts (60) with different contextual use. This study is in line with other research works that highlight the importance of contextually modifying the meaning of technical terms and the need to pay special attention to the particular disciplines. This study highlights the necessity of standardized definitions in such areas as AI and biotechnology because the terminology in these domains is still developing and might not be understood uniformly.

Theoretical and Practical Implications

This paper augments the comprehension of semantic variation in technical language by demonstrating how meanings vary across fields and emphasizing the significance of context in meaning. The outcome is that existing systems of technical terminologies might need to be improved upon to capture the disciplinary diversity (Mokal & Abd Halim, 2023). Practically, the researchers ought to take into consideration the disciplinary context in terms of technical terms to enhance clarity and avoid misunderstanding of interdisciplinary research. The results can facilitate the development of standard terms, in particular in such areas as AI and biotechnology, which enhance communication and cooperation.

VI. Conclusion

In three academic disciplines, such as Engineering, Computer Science, and Social Sciences, the semantic variation of technical terminology is examined in this study. The results indicate that semantic variation of 67% of top 50 terms is quite significant and indicates that various disciplines represent several meanings of the same terms. In different fields of study, the terms model and network define different

things- as physical models in Engineering or machine learning models in Computer Science and conceptual models in the Social Sciences. Secondly, the research indicates that 72 % of variance in meanings of terms in different fields, and there is 15% chance of ambiguity when used across fields. This research has improved the understanding of the technical terminology used in different fields and gives empirical evidence on the contextual dependence. The study aims at the comprehension of how the terms change based on Jaccard similarity and collocational analysis to determine the relation and usage of terms. The interpretation of terms in context is highlighted by using Jaccard similarity coefficients and collocational analysis to examine semantic variation. A theoretical framework is used to study the technical terminology and the significance of focusing on the context of the given discipline to be able to communicate effectively. Future studies will focus on better term recognition and mitigating selection biases with more academic disciplines (medical sciences or environmental studies) and deep learning and advanced NLP methods. To gain a more subtle insight into the changing meaning of terms over time, such approaches as semantic network analysis or cognitive linguistic might be considered. In order to strengthen the interdisciplinary communication, especially in the new areas such as artificial intelligence and biotechnology, one should focus on establishing standard frameworks of technical vocabulary.

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