Textual Analysis of Conceptual Associations in CEFR B2 Level Texts: A Network-based Semantic Representation Approach

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ABSTRACT

Background and Objectives: Lexical cohesion is vital for text comprehension, especially for learners progressing through CEFR levels. While research has focused on logical relations like synonymy and part-whole relationships, conceptual associations remain underexplored. These associations are crucial for cognitive processing and discourse comprehension but appear to be underrepresented in CEFR-B-leveled texts, which may potentially hinder learners' preparation for C1-level demands. This study examines the patterns and prevalence of conceptual associations in B2 texts, their comparison with logical relations, and the impact of topic complexity on their distribution.

Methodology: The study was conducted in two phases, with the initial phase involving the collection of verified B2 level texts. In the second phase, automated analysis via the UCREL Semantic Analysis System (SAS) was used to categorize words into broad conceptual groups, while a manual approach based on Town's (2021) taxonomy was used to verify their actual association. A semantic network analysis based on Yang and González-Bailón's (2017) framework was adapted to examine concept clustering. The semantic network was automatically generated and quantified by the numbers of nodes and clusters present in B2 level texts.

Main Results: B2 texts showed an uneven use of lexical cohesion, relying more on simpler, explicit logical relationships. In all five texts examined, the use of logical relations (such as parent-child and part-whole relationships) outnumbered the use of other conceptual associations. In the five texts combined, logical relations occurred 92 times, whereas conceptual associations occurred 39 times. While this aids initial clarity, it creates a gap for learners moving to higher proficiency levels, where they need to connect ideas less explicitly via modeled B2 texts. Despite the similar totals of cohesive relationships (logical and conceptual associations) from the approximately 20 relationships in each text, B2 texts vary significantly in their use of conceptual association.

Discussions: The dominance of logical relations in B2 texts may limit learners' development of abstract reasoning and inferencing skills, which are critical at higher proficiency levels. While logical relations provide structural clarity, they lack the deeper conceptual connections needed for C1 comprehension. Topic variations also affect conceptual richness, emphasizing the need for intentional text selection. A balanced integration of conceptual associations with logical relations

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could enhance engagement and better align with CEFR descriptors and expectations.

Conclusions: These findings contribute to a deeper understanding of lexical cohesion in B2 texts and emphasize the importance of designing instructional materials that bridge the gap between explicit logical structures and abstract conceptual reasoning. To improve text cohesion and support learners' transition to higher proficiency, B2 materials should incorporate more conceptual associations, particularly entity-based relationships and abstract linkages. By strengthening these connections, reading materials can better align with CEFR descriptors and prepare learners for complex and abstract textual comprehension at the C1 level. Future research should explore effective strategies for integrating conceptual associations into B2 materials and examine their impact on learner comprehension and retention.

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Introduction

Text difficulty has been examined from various angles, including both corpus and computational system approaches. Such automated approaches to texts is unsurprising, as the perception of text difficulty has initially been based on quantitative measures, such as traditional readability formulas like Flesch-Kincaid Grade Level and Flesch Reading Ease (Hiebert, 2002). These readability formulas often rely on word and sentence lengths to measure text difficulty. Difficult text may be simplified in L2 learning materials to make them more appropriate for the target proficiency level of readers based on extant traditional readability formulas serving as the basis of text design and construction.

Text simplification that is based on formulas and computation is called a structural approach (Crossley et al., 2011). This approach contrasts with an intuitive approach, which is more subjective and mostly depends on the author's evaluation of text comprehensibility and discourse processing (Crossley et al., 2011). As a result, the quantitative approach toward understanding text difficulty influences the design of learning materials, the construction of reading comprehension tests, and the quality of written texts used in classes (Fata et al., 2022).

To increase the transparency and coherence of assessing language ability among institutions around the globe, the Common European Framework of Reference for Languages: Learning, Teaching, Assessment (CEFR) is often applied and used to study disparities in text difficulty among readers of differing proficiencies. Ranging from the basic A1 level user to the proficient C2 level user, reading material developers and publishers offer learning resources such as graded reader books for EFL/ESL learners to enhance their reading ability. The CEFR level, often indicated on the cover page of the graded reader book series, is frequently used to indicate text difficulty and appropriateness for learners at different levels.

However, recent findings (e.g., Natova, 2021; Siripol et al., 2025) show a discrepancy among the automated tools in indicating the CEFR level of a written text and recommend qualitative measures in addition to the traditional quantitative measures when written text is analyzed (Natova, 2021). Even with the qualitative approach, assessing CEFR levels using descriptive criteria still produces discrepancies among qualitative descriptions in the criteria or idiosyncrasies between raters (Harsch, 2018). In other words, the concern that Harsch (2018) reported was related to the comparability between tests and assessment context. In this regard, the traditional qualitative criteria for descriptors in assessing difficulty level proposed by Natova (2021) may face discrepancies among interpretations and idiosyncrasies between raters, as Harsch (2018) expressed earlier. This leads to a concern about the current approaches many institutions may adopt when creating an in-house language test, reading materials, and an evaluation of students' reading and writing proficiency levels.

While many linguistic features are used as a metric to indicate text difficulty across levels, research has found that the most significant difference between proficient and exceptional writers lies in their use of semantic association (Towns & Watson Todd, 2019). Semantic association is defined as "…a word or word sequence is associated in the mind of a language user with a semantic set or class, some members of which are also collocates for that user" (Hoey, 2012, p. 24). When referring to semantic relationships, the fundamental linguistic features that can be examined are logical relations (e.g. synonymy, antonymy, hyponymy) and conceptual associations (Towns & Watson Todd, 2019). Traditionally, a conceptual association is known as a 'collocation' (Halliday & Hasan, 2014) and was proposed on the basis of the theory called 'lexical priming' by Hoey (2012), where a given word is primed with another related word/image to produce a target word (Hoey, 2012). Hence, it is not the collocation that is generally viewed (e.g. heavy rain, pay attention, broad daylight). For instance, the word 'dog' can be semantically associated with 'bone' or 'leash' or its semantic coordinate of 'cat'. It could be seen here that the association and coordination highly depend on individual experience, which can differ among learners. To avoid confusion that could occur when semantic association is discussed, the term 'conceptual association' is used instead of 'collocation'. As semantic association is a subjective concept, the framework of analysis may not be widely available in the field of discourse analysis. In addition, an automated tool for capturing conceptual association is currently unavailable since the concept touches upon psychological aspects of human cognition. Wang and Lui (2014) claim that conceptual association is the most problematic linguistic feature to study, which affects how lexical cohesion is examined as it is a part of the lexical cohesion type. This claim is in line with Halliday and Hassan (1976) who noted the challenges in identifying and categorizing various types of semantic association. As a result, very few studies have explored the semantic association that exists at the CEFR-labeled text level (Towns, 2021), and most studies have relied on traditional formulae.

However, as Sung et al. (2015) mentioned, traditional formulae suffer from two major limitations: (1) emphasis on quantifiable traditional linguistic features of written text, which may not reflect the complex cognitive process of readers, and (2) emphasis on the formulae created for first-language writers/readers. Therefore, a study based on a perspective of semantic association that is informed by psychological and cognitive insights and a psycholinguistic framework could deepen our understanding of how textual features can be aligned with the CEFR descriptors. Consequently, this perspective could provide insights into comprehensively assessing lexical cohesion and conceptual complexity across various proficiency stages.

Review of Literature

Text Difficulty and CEFR

Searching for and selecting appropriate texts for L2 learners is vital as it could enhance motivation and learning (Sung et al., 2015). Before producing, searching for, and selecting appropriate materials, language teachers and educators may rely on a particular framework to map out or evaluate text difficulty or text leveling. One of the most popular frameworks used is the CEFR for languages (Europe, 2001). The CEFR is used as a framework for assessing students' language proficiency and is also used to map text complexity (Natova, 2021) to study text difficulty, following its descriptive statements. According to the CEFR, linguistic complexity, text type, discourse structure, physical presentation, text length, and learners' relevance are the major facets in evaluating texts (Europe, 2001).

Linguistic complexity, for instance, has traditionally been used “to gauge proficiency, to describe performance, and to benchmark development and to capture differences between proficiency levels” (Ortega, 2012, p. 218). Although the concept of 'complexity' can refer to many language aspects, such as phonological and morphological complexity, most previous research studies appear to focus on the syntactic aspects of linguistic complexity when text difficulty is evaluated, such as examining the grammar or sentence structure of the text. As syntactic complexity evidently influences text difficulty, syntactic simplification has become a sub-area of text difficulty research. A solid example of syntactic simplification or adapted texts can be captured in the graded reader book series and many ESL/EFL reading materials. Attempts have been made to map the CEFR descriptors to text difficulty level and grade appropriateness. Different syntactic measures used to assess the difficulty of texts have received great attention over the last decade due to the advancement in computational linguistics and discourse processing, offering many automated text-processing mechanisms (Graesser et al., 2004).

Notwithstanding the widespread use of automated tools to measure CEFR levels of text, current existing automated tools show inconsistent results (Natova, 2021; Siripol et al., 2025). A study conducted by Natova (2021) provides a springboard for further investigation into the qualitative aspects of text analysis, especially in relation to the psychological aspects of readers, such as semantic complexity and its roles in connecting concepts and ideas within a text of different CEFR levels. Few studies focus on semantic complexity in texts compared to syntactic and morphological complexity of different CEFR text levels, as there is no agreed-upon framework or methods to initiate text analysis in measuring semantic complexity (Towns, 2021). However, a recent study by Towns and Watson Todd (2019) found that semantic complexity, specifically semantic association, plays a large role in distinguishing between proficient and exceptional written texts. Their innovative study strongly indicates that conceptual association and its influence on text difficulty provide exciting parameters for a further qualitative investigation of text difficulty analysis. Currently, the role of conceptual association clustering, an abstract cognitive-semantic demand, remains underexplored within the CEFR. This leads to a limited understanding of how such demands are integrated. Furthermore, the basis for classifying reading levels and text difficulty within the CEFR is often unclear, particularly when considering the psycholinguistic validity of its descriptive banding system of A1 to C2.

Semantic Association

Hoey (2012) discusses semantic association as part of a study called *lexical priming*, which is a linguistic theory that combines corpus linguistics with psycholinguistic experiments. This theory explores how words are linked in our minds based on previous experiences and language use. Because both psychological processes and language data are involved, the study of semantic association extends across cognitive science, computer science, and psycholinguistics. However, the term 'semantic association' varies across different disciplines. In cognitive and computer science, it is called "semantic association" (Griffiths et al., 2007). In linguistics, it is often referred to as "collocation", "general heading" (Halliday & Hasan, 1976), or "conceptual association" (Towns, 2021; Towns & Watson Todd, 2019; Yan et al., 2023). Despite the differing terms, the underlying idea is about how words or concepts are related. Since there is no universally accepted definition of this phenomenon, this study will consistently use the term "conceptual association” to avoid confusion.

The study of conceptual association falls under cross-disciplinary areas of both linguistics and cognitive psychology, especially when the influence of text coherence is involved. The connectedness of concepts is traditionally viewed from the perspective of cohesion and coherence (Towns & Watson Todd, 2017). According to Halliday and Hasan (1976), there are two major types of cohesion: (1) grammatical and (2) lexical cohesion. The conceptual association falls under lexical cohesion. Crossley (2020) mentioned that text cohesion is text-based, whereas coherence is reader-based. In other words, cohesion can be identified and analyzed by examining the frequency of cohesive devices used throughout the text. On the other hand, coherence is psychological, hence more challenging to objectively pinpoint. Linguists have long researched the connectedness of concepts within texts, since traditional measures of writing quality often rely on the identifiable surface-level cohesive devices that occur. Both cohesion and coherence can be viewed as a continuum of cohesion of explicit meanings to the coherence of implicit meanings. In other words, coherence involves both surface textual features and psychological aspects of the reader's background knowledge to make connections among concepts. Therefore, examining text quality or linguistic features through text-level patterns must consider conceptual association to see how proficient or intermediate-level writers create coherence through concepts.

Written text quality has been studied based on how different cohesive devices are used (Chanyoo, 2018; Crossley, 2020). The methods of identifying and categorizing cohesive devices in text are well-established, and recent findings reveal that surface cohesive features such as reiteration and conjunction are among the devices widely deployed in text construction (Akmilia et al., 2022; Chanyoo, 2018). However, conceptual associations have often been ignored due to their labor-intensive process of manually identifying and categorizing them. Towns and Watson Todd (2019) recently found that conceptual association plays a major role in making differences between proficient and exceptional writing texts. Exceptional writers (e.g., Pulitzer Prize winners) appear to use fewer grammatical and other lexical cohesive devices compared to proficient writers, and conceptual association was shown to play a larger role in creating cohesion in the text as a result (Towns & Watson Todd, 2019).

Later, another related formative study of a semantic network of semantic representation between high and low text levels indicated differences in the connection of conceptual association as manifested in a comparison of A1 and C1 texts (Siripol & Towns, 2021). The study supports Crossley's (2020) and Halliday and Hasan's (1976) claim that semantic dependency is one of the elements that can influence text cohesion, which relates to the interconnectivity of text segments. Nonetheless, semantic network representation of a specific text difficulty level is very scarce in current literature, and whether specific text difficulty levels are associated with particular patterns of conceptual association constitutes an important question. Research in cohesion and coherence has often focused on those that are straightforward to identify, most notably including reference, substitution, ellipsis, and conjunctions. Therefore, the least understood and intuitive type of lexical cohesion (i.e., conceptual association) needs to be explored to not only fill in the gap in the hypothesis of the influence of conceptual association on textual coherence but also contribute to the assessment of text difficulty and quality among different proficiency levels of readers and writers.

A Brief Overview Semantic Association Taxonomy Development and Approaches to Semantic Representation

Since identifying semantic features of text can be subjective in nature, this led to the development and proposal of taxonomies by different researchers from a cognitive psychology perspective. The largest taxonomy found in the literature is that of Wu and Barsalou (2009). Associated with cognitive psychology involving human subjects, the taxonomy was developed through a stimulus-response experiment. In a stimulus-response experiment, a concept (stimulus) is given to the participant, who then responds with a concept associated with it. Wu and Barsalou's (2009) taxonomy contains 37 categories, which are subdivided into five microcategories with four macro-categories covering conceptual associations (i.e., entity properties, situation properties, introspective properties, and miscellaneous). Later, this taxonomy was adapted on the basis of reliability by Bolognesi et al., (2017). Bolognesi et al. (2017) then reduced the 37 categories to 20 under three macro-categories for conceptual association. A part of this revised taxonomy is shown in Table 1.

Table 1. Sample of the Adapted taxonomy of Bolognesi et al. (2017) based on Wu & Barsalou (2009)

Macro-category	Nested Category	Nested Category description	Examples (with concrete and abstract instances	Counter Example (with concrete and abstract instances, if applicable and relevant) and their correct coding
Concept properties (E) Properties of a concrete or an abstract entity	Perceptual properties (E-Perc)	Sensory properties of the concepts, including visual features, smell, sound, texture, taste	Seagull-white Seaweed-slimy Turtle-hard Fruit-Sweet	Situation-stick
	Non-perceptual properties (E-sys)	A global (objective) systemic property of an entity or its parts, including states, conditions, abilities, traits	Plastic spoon-cheap President-important Kid-development	Swan-beautiful Sweater-comfortable Toy-fun

Apart from the field of cognitive psychology, a taxonomy developed from a multidisciplinary field known as terminology processing also emerged (Sager, 1990). Semantic relations and relationships of terms or concepts were categorized into three macro-categories: (1) generic relationships, (2) partitive relationships, and (3) complex relationships.

The taxonomy development of Wu and Barsalou (2009), Bolognesi et al. (2017), and Sager (1990) led to a more recent development of semantic relationship taxonomy by Towns (2021). In Towns' (2021) taxonomy, previous taxonomies proposed from the field of cognitive psychology and terminology processing were adapted and combined to form a new semantic relationship taxonomy, particularly for classifying and categorizing logical relations and conceptual associations. A broad-based semantic relationship taxonomy by Towns (2021) was developed with the aim of using it for linguistic analysis of general texts. Three main categories were derived, including logical relations, activities, and entities. A pilot study was also conducted by Siripol and Towns (2021) with graded readers at different levels to determine the relationship of each word-pair link. Towns (2021) recommended the use of both quantitative and qualitative studies to investigate the literary aspects of a text. Table 2 shows the taxonomy proposed in Towns' study (2021).

Table 2. The New Towns (2021) Conceptual Association Taxonomy

Category	Word 1	Word 2	Natural Language Phrase
Logical relations			
Synonym	Bike	Bicycle	X has the same meaning as Y
Antonym	Love	Hate	X is the opposite of Y
Parent-Child	Car	Vehicle	X is a type of Y
Sister terms	Pepper	Salt	X and Y have the same parent
Part-Whole	Window	House	X is part of Y
Activities			
Agent	Teacher	Teach	X does Y (activity)
Instrument	Writing	Pencil	X (activity) is done using Y (obj)
Recipient	Teach	Student	X (activity) to Y (changed)

Table 2. (Cont.)

Category	Word 1	Word 2	Natural Language Phrase
Theme	Teach	Subject	X (activity) to Y (unchanged)
Location	Teach	Classroom	X (activity) occurs at Y (location)
Output	Manufacture	Product	X (activity) outputs/results in Y
Entity			
Property	Table	Wood	X has a property of Y
Origin	Watermelon	Ground	X comes from Y
Location	Car	Garage	X is contained/located in Y
Time/Event	Watermelon	Picnic	X is used in event Y
Measurement	Light	Watt	X is measured in Y
Contingency	Smoke	Pollution	X causes/requires/depends on Y
Participants	Child	Toy	X (person) interacts with Y (obj)
Abstract	Clothing	Protection	X (person/obj) interacts w/abstract concept Y
Object	Grass	Sun	X (obj) interacts with Y (obj)

The Taxonomy of Towns (2021) provides a framework that researchers and discourse analysts could use for general written texts. However, the need for an approach to represent semantic association is vital when organizing the connection of associated concepts. According to Griffiths et al. (2007), there are three major approaches to semantic representation: a semantic network, a semantic space, and the topic model (Griffiths et al., 2007). In a *semantic network*, nodes and edges represent words or concepts and are indicators for semantic association. An example of how concepts are illustrated as a semantic network representation of the concepts relating to ‘library’ is shown in Figure 1. The second approach, *a semantic space,* is focused on representing points and the proximity of semantic association. The closer two words are in meaning, the smaller the distance between them in semantic space. Figure 2 illustrates an example of a semantic space of words found together in the same textual unit (like a sentence or paragraph). The last approach is the *topic model*, where words are listed from high to low probability under a specific topic. This is shown in Figure 3. The matrix on the left shows the probability of each word belonging to each of the three topics. The three columns on the right list the words within those topics, ranked by their likelihood. As this paper aims to explore textual patterns of conceptual connection of a specific CEFR text, the network-based approach was selected.

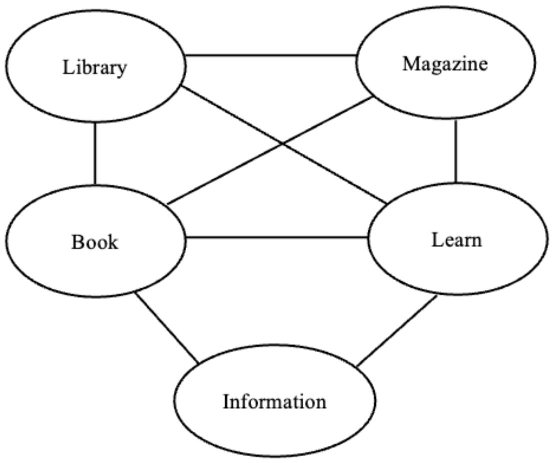

Figure 1 A Semantic Network Representation (Adapted from Griffith et al., 2007)

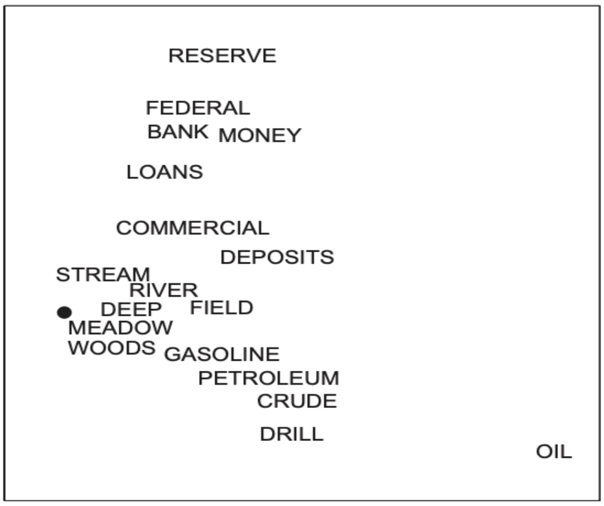

Figure 2 A Semantic Space Representation (Taken from Griffith et al., 2007)

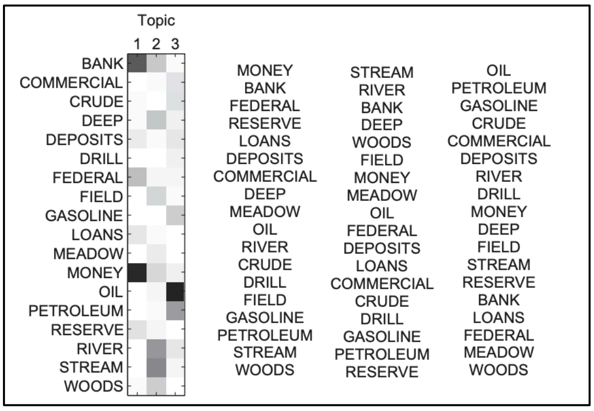

Figure 3 A Topic Model Representation (Taken from Griffith et al., 2007)

From Figure 1, the concept of 'library' can be associated with 'book,' 'magazine,' and 'learn.' Readers are expected to come across these concepts. Although 'book' can also be a verb that means 'to arrange something,' readers intuitively recognize 'book' as a written or printed work. Readers recognize the meaning of 'book' due to the context of the situation and the semantic relationships with other words. The concept of 'book' then is semantically associated with 'information,' 'learn,' and 'magazine' in a story. It could be implied from the semantic network in Figure 1 that the story involves a character reading something at a library or searching for some information from the library. This demonstrates conceptual association as a cohesive device, influenced by contextual factors, to make the story coherent even with limited use of other traditional cohesive devices such as coordinating conjunctions.

It is currently unclear what role conceptual associations play in texts, especially those designed for readers of different language levels. This is because conceptual association must be worked out manually. Since it has been shown that conceptual association plays a role in the text, further research is needed in this area. Although the study of Siripol and Towns (2021) provides an initial finding of conceptual association differences in high and low CEFR level texts, the purpose was only to verify and test out the newly developed and proposed taxonomy of Towns (2021). Traditional measures using automated programs are still a major approach since they can easily capture the surface-level cohesive devices. As a result, many previous studies focus on identifying surface cohesive devices such as repetition, reiteration, and conjunctions. To fill in the gap, this research aims to answer the question: What conceptual association clusters and types are found in written CEFR B2 level texts?

Method

This section is divided into two subsections, outlining the method for capturing conceptual associations from texts. Phase 1 focused on text preparation, which included recruiting B2 texts and ensuring their reliability based on the corresponding CEFR descriptors. Phase 2 involved adapting text analysis procedures by using an automated program in conjunction with Towns' (2021) taxonomy framework. This phase included both automated and manual approaches to identify and categorize conceptual associations. This was to ensure the reliability of the selected concepts during the manual analysis stage.

Phase 1

Text Recruitment and Preparation

Texts were recruited from an open-source website specifically designed for language teachers and learners (www.lingua.com). The website offers reading materials separated into different levels of CEFR, ranging from A1 to C1, with comprehension questions for each text. Reading comprehension materials from the website claim to be authentic, incorporating cultural aspects for readers in English and 15 other languages. Table 3 shows the criteria for text recruitment, which concerns accessibility and copyright, text source, CEFR level indication, minimum word count, and text structure/genre.

Table 3. Criteria for Text Recruitment

Criteria for Text Recruitment	
Accessibility and Copyright	An article must be accessible to the public online, offering both a basic (free) account and/or paid account option Copyright of an article does not prohibit readers/users from analyzing the discourse content
Text Source	An article must be from the same source (publisher)
CEFR Level Indicator	An article that has a clear indicator of B2
Minimum Word Count	An article that contains a word count of at least 150 words
Text Structure/Genre	Descriptive texts

Validity and Reliability of CEFR Texts

To validate that the texts recruited aligned with a specific CEFR level, all texts were selected from the same source (www.lingua.com) with a clear CEFR indicator. Since this study is only focusing on CEFR texts at the B2 level, 10 texts were randomly selected for an Item Objective Congruence (IOC) using five automated instruments. One instrument was based on a large language model and the following four were specifically designed to level text into CEFR: ChatGPT 3.5, Cathoven AI, Global Scale of English Text Analyzer (Pearson), Text Inspector, and Text Analyzer (Road to Grammar). The study included texts that surpass 60% similarity index or surpass at least three out of five CEFR analyzer tools that indicate the B2 level. While no specific precedent exists for this exact threshold in the literature, the choice was informed by the general practice in psychometric and linguistic validation studies, where agreement thresholds are used to ensure the reliability of classifications (Ismail & Zubairi, 2022). A number was assigned to the CEFR to calculate for the mean, median, mode and standard deviation (1 = A1, 2 = A2, 3 = B1, 4 = B2, 5 = C1, and 6 = C2). Tables 4 and 5 show the result of the generated CEFR based on the five CEFR analyzers and a summary of the descriptive statistics information.

Table 4. Automated CEFR Analyzer for B2 Texts

Title of Text	ChatGPT 3.5	Cathoven AI Version 2.0 (General Level)	Global Scale of English (GSE) Text Analyzer (Pearson)	Text Inspector (Overall Lexical Scale)	Text Analyzer (Road to Grammar)
1. Las Vegas	3 (B1)	3 (B1)	4 (B2)	5 (C1)	4 (B2)
2. Liechtenstein	3 (B1)	3 (B1)	4 (B2)	5.5 (C1+)	4 (B2)
3. Trip to New York	3 (B1)	3 (B1)	3.5 (B1+)	4.5 (B2+)	3 (B1)
4. Santa Claus around the World*	3 (B1)	4 (B2)	4.5 (B2+)	5 (C1)	4 (B2)
5. Boston*	4 B2	3 (B1)	4.5 (B2)	5.5 (C1+)	4 (B2)
6. Cruise Ships: Floating Marvels of Marine Life	3 (B1)	3 (B1)	4.5 (B2+)	5.5 (C1+)	6 (C2)
7. Benjamin Franklin and the Kite*	4 (B2)	4 (B2)	4 (B2)	6 (C2)	5 (C1)
8. Hot Air Balloons: A Fun History*	4 (B2)	4 (B2)	4 (B2)	6.5 (C1+)	5 (C1)
9. The longest and most scenic Train Ride*	4 (B2)	4 (B2)	4 (B2)	5 (C1)	4 (B2)
10. Animal	4 (B2)	3 (B1)	4 (B2)	6 (C2)	5 (C1)
Mean (CEFR Level)	3.50 (B1+)	3.40 (B1)	4.05 (B2)	5.55 (C1+)	4.25 (B2)
Median (CEFR Level)	3.50 (B1+)	3.00 (B1)	4.00 (B2)	5.50 (C1+)	4.00 (B2)
Mode (CEFR Level)	3.00 (B1)	3.00 (B1)	4.00 (B2)	5.50 (C1+)	4.00 (B2)
Standard Deviation (SD)	0.53	0.52	0.15	0.50	0.52

*Surpasses the 60% similarity index

Table 5. Derived texts to be analyzed based on those passed the IOC of 60% similarity index

Texts	Title (CEFR B2)
1	Santa Claus around the World
2	Boston
3	Benjamin Franklin and the Kite
4	Hot Air Balloons: A Fun History
5	The longest and most scenic Train Ride

Phase 2

Phase 2 diverges into several stages of analysis, involving both automated and manual approaches. This phase adapts the framework of semantic network analysis of Yang and González-Bailón (2017). An automated approach was added prior to the manual analysis to adapt the semantic network analysis. In the automated stage, the UCREL Semantic Analysis System (SAS) was used to automatically identify and categorize semantically related words. This is a software tool used for automatic semantic analysis of text. The system can assign semantic tags to words and phrases, categorizing them based on their meaning, and help the analysis of text beyond just the surface level by providing insights into the underlying semantic content. This was to provide researchers with an initial and reliable broad-based category of concepts. Although the SAS can provide a grouping of words, it does so in groups where the connection between words is unclear. This means that the listing of words generated does not provide linkage information of association among words within the generated list. Table 6 demonstrates a sample of the results generated by the UCREL SAS.

Table 6. Sample Result Generated by the UCREL Semantic Analysis System

Semantic group provided by UCREL Semantic Analysis System	Architecture, housing, and the home	Money and commerce in industry	Science and technology	Time
Words in each group	house apartment doors room addresses home chairs	business office clients work working job staff	technology laptop computers cyber screens program passwords	day years night hours Sunday evening Monday

In a manual approach, Yang and González-Bailón's (2017) framework of semantic analysis provided a basis for textual analysis in order to answer two major questions: (1) what semantic units need to be represented, and (2) what relationships need to be mapped. Since the automated instrument and taxonomy used in this study are suitable at the lexical-semantic level, concepts and words at a lexical level as a semantic unit were the focus. For the second consideration, to map the semantic relationship, a network mapping relationship method was adapted to Towns' (2021) taxonomy (Table 2) to identify the relationship among concepts. The list of associated words generated by the UCREL was transferred to the network mapping semantic relationship matrix to validate the association. The benefit of this approach over the lexical chain approach is that concepts occurring in a text can be associated with multiple concepts, branching out in a network-like fashion. A sample of a network matrix mapping relationship can be seen in Figure 4. The first column and the first row of the network matrix contain the same words generated by the UCREL SAS. The researchers manually ensured this by checking the actual relationship within the word list. For instance, the words 'house' and 'door' are semantically associated in general (part-whole relationship) but may not be true in the story. The word 'door' may be associated with 'apartment' instead. Therefore, the use of UCREL SAS alone cannot verify the actual semantic relationship that takes place in the story. The matrix was adapted from Yang and González-Bailón's (2017) matrix. In order to confirm the relationships that actually occur in a text, the researcher followed the framework as summarized in Figure 5.

	Technology	Laptop	Computer	Cyber	Screen	Program	Password	Hacker
Technology		✓		✓		✓		✓
Laptop			✓			✓		✓
Computer					✓	✓		✓
Cyber						✓	✓	✓
Screen								
Program								✓
Password								✓
Hacker								

Figure 4 An adaptation sample of a network matrix in mapping semantic relationships

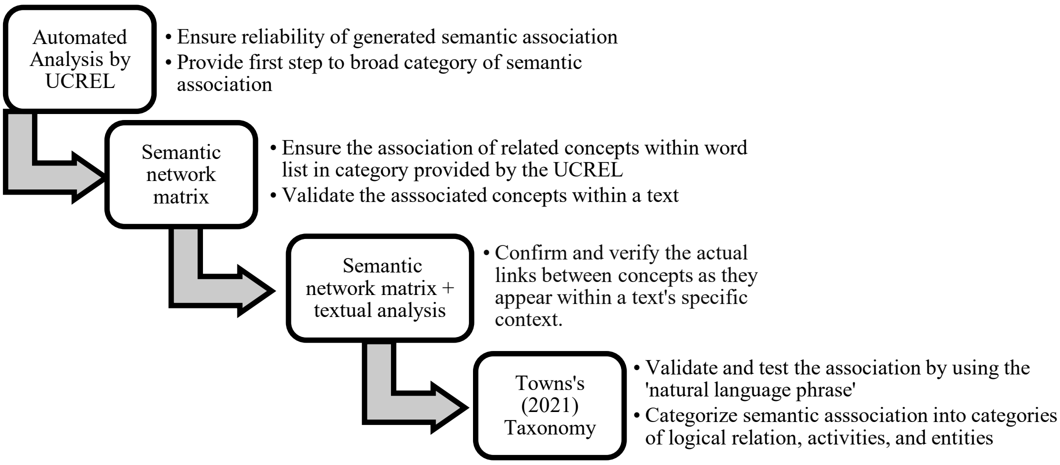

Figure 5 Major Stages of Phase 2

In the final step, Towns' (2021) taxonomy was used to validate, test, and categorize semantic associations into types. The semantic association taxonomy contains three major categories and 20 subcategories. One major advantage of Towns' (2021) taxonomy is that it provides a natural language phrase for researchers to test out the association, which makes the identification and categorization quite straightforward.

Data analysis

A semantic network analysis framework (Yang & González-Bailón, 2017) was adapted to analyze the data. According to the semantic network analysis framework by Yang and González-Bailón (2017), there are three levels of analysis: (1) individual, (2) interpersonal, and (3) collective. Table 7 summarizes this framework. The different features between doing Concept-to-Concept and Actor-to-Actor depend on the primary research goal. If the primary goal is to illustrate connective nodes into themes, ideas, keywords, topics, or how ideas are related, Concept-to-Concept would be suitable. This is because the Concept-to-Concept application focuses on the structure and content of the discourse itself. If, however, the analysis focuses on analyzing semantic similarity or overlap in discourse between actors or to illustrate connective nodes into individuals, organizations, or groups, then the Actor-to-Actor would be appropriate. The result from the Actor-to-Actor application would provide the clustering of actors based on a discourse.

With three levels of analysis, this study closely aligns with Concept-to-Concept as a type of application. Figure 4 provides examples of the representation of cognitive mapping. This is similar to Griffiths et al. (2007), who refer to this as a semantic network representation or a network-based semantic representation.

Table 7. Semantic Network Analysis Framework from Yang and González-Bailón (2017)

Level of analysis	**Type of application**	
	Concept-to-concept	Actor-to-actor
Individual	Cognitive mapping (figure 4)	-
Interpersonal	Discourse network analysis-concept congruence/conflict network	Discourse network analysis-actor congruence/conflict network; discursive fields
Collective	Salience and framing	Future research

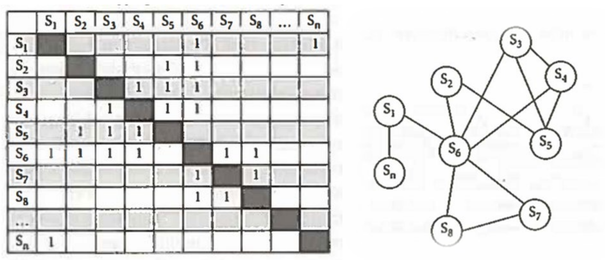

Figure 4 Example of Network Mapping Semantic Relationship
(Taken from Yang and González-Bailón 2017 p. 329)

In adapting the semantic network analysis framework of Yang and González-Bailón (2017) by combining Towns' (2021) taxonomy, semantic associations were further quantified based on several nodes (connected by edges) and the size and number of clusters. In the first dimension, nodes and edges were manually counted to represent the semantic relationship between or among concepts (Griffiths et al., 2007), and it could reflect the phenomenon of semantic priming (McNamara et al., 1996). This is an advantage in explaining various phenomena, including the topic of textual coherence in this study. Since nodes of relationships can be quite complex or connected to many other concepts, the second dimension considered was the size and number of clusters. Each cluster represents a theme of a broad concept occurring in B2-level texts. The cluster size depended on the number of nodes within one cluster of concepts. The number of clusters in B2-level texts can provide quantitative data for researchers to examine CEFR B2 semantic textual patterns. Another quantitative metric to consider is that of Towns' (2021) taxonomy, where relationship types were manually counted. This stage of analysis provides not only a network-based semantic representation but can also be quantified into specific types or sets of relationships.

Findings and Discussion

A network-based semantic representation from texts 1 to 5 can be seen in Figures 6 to 10. The results are automatically generated by the graph editor by CS Academy program and are turned into quantitative data summarized in Table 8.

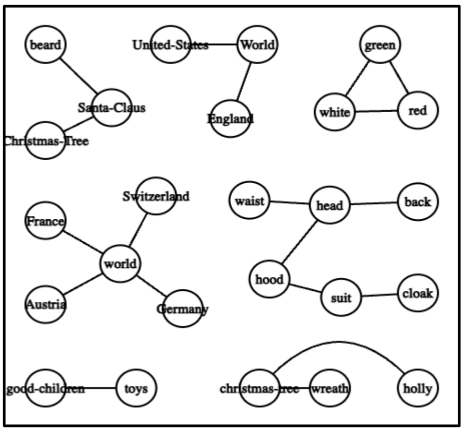

Figure 6 Semantic Network of Text 1 (Santa Claus around the World)

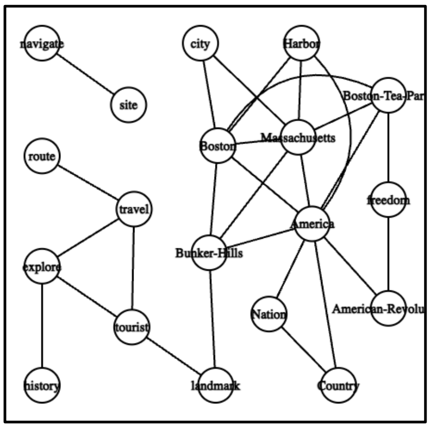

Figure 7 Semantic Network of Text 2 (Boston)

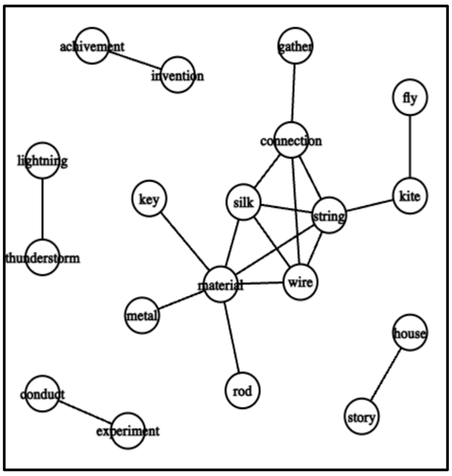

Figure 8 Semantic Network of Text 3 (Benjamin Franklin and the Kite)

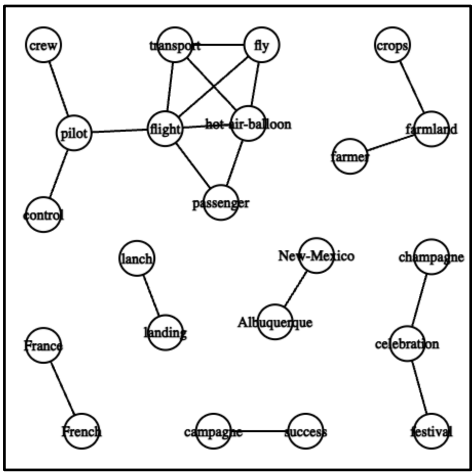

Figure 9 Semantic Network of Text 4 (Hot Air Balloons: A Fun History)

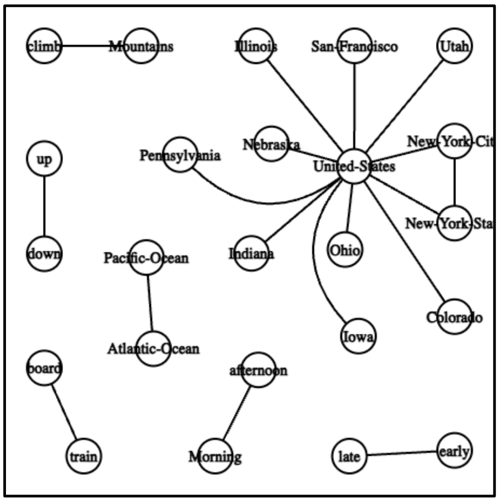

Figure 10 Semantic Network of Text 5 (The Longest and Most Scenic Train Ride)

Table 8. Number of words in each cluster sorted by node sizes 2-17

Size	Cluster of Text 1 (Santa Claus Around the World)	Cluster of Text 2 (Boston)	Cluster of Text 3 (Benjamin Franklin and the Kite)	Cluster of Text 4 (Hot Air Balloons)	Cluster of Text 5 (The Longest and Most Scenic Train Ride)
2	1	1	4	4	6
3	4		-	2	-
4	-	-	-	-	-
5	1	-	-	-	-
6	1	-	-	-	-
7	-	-	-	-	-
8	-	-	-	1	-
9	-	-	-	-	-
10	-	-	-	-	-
11	-	-	1	-	-
12	-	-	-	-	1
13	-	-	-	-	-
14	-	-	-	-	-
15	-	-	-	-	-
16	-	-	-	-	-
17	-	1	-	-	-
Total Clusters	**7**	**2**	**5**	**6**	**7**

The sizes of the network clusters in Text 1, "Santa Claus around the World," to 5, "The Longest and Most Scenic Train Ride," are summarized in Table 8. The total number of clusters in Texts 1 through 5 is consistent, except for Text 2, "Boston," in the total number of clusters. Each text contains at least one two-node cluster, with the frequency of total clusters ranging from highest to lowest as follows: Text 5 and 1 (tied), Text 4, Text 3, and Text 2 (the lowest). The largest cluster in each text varies, with Text 1 featuring a 6-node cluster, Text 2 a 17-node cluster, Text 3 an 11-node cluster, Text 4 an 8-node cluster, and Text 5 a 12-node cluster. Although Text 2 has only two clusters, it contains the largest single cluster, a 17-node cluster.

Several discussion points regarding the interaction of concepts and textual coherence can be drawn from the results in Table 8. First, while the total number of clusters across the B2 texts appears inconsistent, this variation is not as significant as the node clusters' size. A closer examination of the node sizes suggests that the number of clusters provides insight into how different topics are introduced and maneuvered throughout the texts. However, the actual interplay of coherence is more strongly tied to the size of the node clusters. For example, although Text 2 "Boston" has the fewest clusters overall, it contains the largest node cluster (i.e., 17 nodes). This suggests that despite its smaller number of clusters, Text 2 "Boston" manages to group related concepts into larger, more complex clusters, which may indicate a more tightly woven thematic structure. This largest cluster's size and thematic focus likely reflect the dominant concept in Text 2, "Boston." Further comparison with the titles of the texts supports this interpretation. Text 1's title, "Santa Claus Around the World," contains more than one concept, and so do the titles of Text 3, "Benjamin Franklin and the Kite," and Text 5, "The Longest and Most Scenic Train Ride." This difference in title complexity suggests that Text 2, "Boston," with its singular focus on the city of Boston, may naturally lend itself to a larger, more densely connected cluster of related ideas, reinforcing the prominence of this concept for the reader.

An important factor that explains the variation in cluster size across the B2-level texts is that of the themes or topics of the texts themselves. Texts of different themes tend to have different demands in terms of the number and size of lexical clusters, and this can impact the overall organization of concepts within the text. For example, in Text 2 “Boston”, which focuses on a specific topic (Boston), there is a marked tendency toward fewer but larger lexical clusters, particularly the 17-node cluster. This large cluster suggests that the text is organized around a highly cohesive set of related concepts or themes, where specific lexical items (such as "Boston," "city," and "history") are strongly associated with each other through lexical priming**.** The lexical priming theory posits that exposure to certain word combinations in specific contexts increases the likelihood of these words appearing together in subsequent discourse (Hoey, 2012). In the case of Text 2 “Boston,” the repeated exposure to key terms related to Boston primes readers to expect and recognize these terms in close association, forming larger clusters. These larger clusters reflect a coherent, focused thematic structure that is typical of more informational or descriptive genres, where the content revolves around a single central concept. Similarly, Text 5, “The Longest and Most Scenic Train Ride,” which may include various details about a scenic train ride, also likely contains several clusters that reflect a diversity of related concepts (e.g., "train," "scenery," "landscape"). This aligns with the descriptive or narrative nature, where a range of related lexical items is needed to convey the richness of the experience. While these smaller clusters are thematically connected, they might not be as tightly packed as the single, large cluster in Text 2, reflecting a less focused but still coherent thematic development. In addition, the differences between Text 2 and the other texts further support the role of lexical priming in shaping textual coherence (Hoey, 2012).

Table 9. Conceptual Association Relationship Types in B2 Texts

Relationship Type	Text 1 Santa Claus Around the World	Text 2 Boston	Text 3 Benjamin Franklin and the Kite	Text 4 Hot Air Balloons	Text 5 The Longest and Most Scenic Train Ride
Synonym	-	1	-	2	-
Antonym	-	-	-	1	3
Parent-Child	-	3	6	1	-
Sister Terms	7	-	-	5	1
Part-Whole	7	11	2	-	12
Total logical relations	14	15	8	9	16
Agent	-	2	-	1	-
Instrument	-	-	-	-	-
Recipient	-	-	-	-	-
Theme	-	5	2	1	2
Location	-	-	-	-	-
Output	-	2	-	-	-

Total Activities	0	9	2	2	2

Table 9. (Cont.)

Relationship Type	**Text 1 Santa Claus Around the World**	**Text 2 Boston**	**Text 3 Benjamin Franklin and the Kite**	**Text 4 Hot Air Balloons**	**Text 5 The Longest and Most Scenic Train Ride**
Property	-	-	-	-	-
Origin	-	-	-	-	-
Location	2	-	-	2	-
Time/Event	-	-	-	2	-
Measurement	-	-	-	-	-
Contingency	-	-	2	-	-
Participants	2	-	-	3	-
Abstract	-	-	5	2	-
Object	1	-	3	-	-
Total Entities	5	0	10	9	0
Total all relationships	**19**	**24**	**20**	**20**	**18**

Table 9 presents a detailed analysis of the semantic relationships across the five B2 texts. The results show a general consistency in the total number of relationships, with Text 1 containing 19 relationships, Text 2 having 24, Text 3 and Text 4 each displaying 20, and Text 5 showing 18. Among these relationships, logical relations dominate all five texts, followed by activities and entities. According to Europe (2001), the CEFR B2 descriptor (global scale), learners can do the following:

> Can understand the main ideas of complex text on both concrete and abstract topics, including technical discussions in his/her field of specialisation. Can interact with a degree of fluency and spontaneity that makes regular interaction with native speakers quite possible without strain for either party. Can produce clear, detailed text on a wide range of subjects and explain a viewpoint on a topical issue giving the advantages and disadvantages of various options (p. 24).

To truly understand the main ideas of complex texts, especially those dealing with abstract topics, readers should ideally be exposed to a variety of conceptual association types and clusters. However, language teachers defining "complex text" may interpret this phrase differently, often focusing solely on complex sentence structure or intricate sets of ideas. According to the findings in Table 9, examining texts appropriate for learners engaging with complex and abstract topics, certain types of conceptual association, specifically those related to entities and activities, were limited in use when compared to the total number of logical relations. This imbalance suggests that B2 texts, which aim to prepare learners for more advanced content at the C1 level, place more emphasis on simpler, more explicit relationships like part-whole and parent-child relationships, which are easier to comprehend and identify. While this focus on logical relations may serve to enhance clarity and cohesion at a foundational level, it also highlights a potential gap in preparing learners for the more complex, abstract connections required at higher proficiency levels. North (2005) mentioned that language users at the C1 level should be able to organize and link "most ideas appropriately, with or without explicit linking words" (p. 58). This supports the idea that learners are expected to engage with more sophisticated texts that require the ability to link conceptual domains. The underrepresentation of conceptual associations in B2 texts could hinder learners' development of the cognitive skills needed to navigate these more intricate relationships. This trend aligns with existing research, which often emphasizes lexical cohesion in terms of relationships like synonymy, antonymy, and hyponymy, which are easier to assess and operationalize in language teaching (Sihombing et al., 2024). As a result, there is a need to integrate more conceptual associations into B2 texts to better prepare learners for the challenges of higher-level academic and professional discourse, where the ability to synthesize and connect complex ideas is essential.

The high number of entities in Text 3 (10 entities) and Text 4 (9 entities) can be attributed to the nature and content of these texts, which likely feature a greater variety of topics or more detailed depictions of people, places, objects, or events. Descriptive texts may naturally demand the introduction of a wide range of entities to establish a comprehensive understanding of the subject matter. For example, the texts cover topics such as travel, history, or cultural events. In those cases, they may include numerous specific entities—such as locations, historical figures, landmarks, or even abstract concepts—that require clear identification and reference throughout the discourse. The increased number of entities in these texts could also reflect a higher degree of conceptual elaboration, where the relationships between different entities become central to the text's development.

In contrast, texts with fewer entities might focus on more general or abstract ideas, where specific referents are not as necessary. This distinction highlights how the theme and topic complexity can influence the number and type of conceptual associations present in a text. As such, Texts 3 and 4 use a broader range of entities to support more intricate thematic development, making these texts richer in terms of lexical cohesion through the identification and interplay of various conceptual referents.

Relating to the size and clustering of nodes found in B2 texts, a development for improving the precision of text alignment within the CEFR may lie in the conceptualization of a novel conceptual density index. This index can possibly be derived from the quantitative analysis of node size and clustering within textual representations, where concepts serve as nodes and their semantic associations as the connecting edges. Unlike traditional readability metrics that primarily focus on surface-level linguistic features, this proposed approach directly addresses the CEFR's emphasis on comprehending complex and abstract topics, particularly relevant at higher proficiency levels such as B2. By quantifying the density of interconnected ideas, for instance, through metrics like the number of associations per concept (node size) and the degree of interconnectedness within conceptual groups (clustering), this index could offer a more granular and psycholinguistically valid measure of the cognitive demands inherent in a given text. Such a measure may hold significant potential for refining the objective classification of CEFR-aligned materials and for providing invaluable insights to material developers and language educators in designing content for specific proficiency objectives.

Implications of the Study

This study examined the occurrence of conceptual associations using a network-based semantic representation as an approach to examine how concepts are connected to create coherent concepts for readers, particularly for learners at the B2 proficiency level. The lack of conceptual association occurred in reading materials may hinder learners' readiness in moving forward to a higher proficiency level, such as C1. This study calls for balanced text designs combining logical and conceptual connections to better prepare learners for language learning. In other words, authors should consider balancing the explicit causal or sequential links and implicit connections that require readers to infer relationships between concepts. Whether this is done through using thematic links or figurative language, language learners could feel more prepared when advancing to the C1 level where the ability to comprehend implicit meaning or to use implicit organizational patterns is described in the C1 descriptor.

In addition, this study offers a practical starting point for EFL/ESL educators and students, providing initial examples of conceptual association features found in B2-level texts. The aim is to encourage a shift towards deeper text comprehension that could be used in English reading courses. For instance, consider how questioning techniques can be adapted in the classroom. Instead of focusing solely on recall with questions such as "what happened next?", teachers can consider asking higher-order thinking questions during-and-after reading exercises or discussions. Asking "Why do you think the author connected X with Y?" not only prompts students to explore implied relationships but also encourages them to critically evaluate the information presented in the text. This fosters a more analytical approach to reading.

When assessing language proficiency, educators and teachers may expect to see a growing density and complexity of conceptual associations as learners advance through the CEFR levels (A1-C2). This understanding should directly influence how EFL/ESL reading materials are designed. Instead of solely relying on metrics like sentence length or verb tenses to map text difficulty, conceptual association can be integrated as a key qualitative criterion. Furthermore, when evaluating text quality based on cohesion and coherence, teachers can go beyond surface-level cohesive devices like conjunctions to specifically examine the underlying conceptual associations.

Limitations of the Study

The study focused on examining the conceptual associations presented in CEFR B2 descriptive texts rather than generalizing all B2-level materials. It must be noted that the findings are limited by the reliance on a small sample of texts sourced exclusively from a single platform (www.lingua.com), which may not capture the diversity of B2-level materials globally. Texts from various genres or sources could display different patterns of conceptual associations. The use of manual analysis to identify and categorize these associations could also pose subjectivity and potential inconsistencies, further complicated by the lack of standardized methods for defining conceptual associations. Despite these limitations, the study aligned with the CEFR framework by highlighting lexical cohesion as a key feature at the B2 level to refine text analysis for better alignment with proficiency descriptors.

Recommendations for Future Studies

Future studies could broaden the text sample to include a wider variety of CEFR B2 texts from different genres, themes, and sources, offering a more comprehensive understanding of how conceptual associations appear across diverse written discourse. Developing a standardized framework for identifying conceptual associations is also recommended to enhance reliability and consistency, involving clear guidelines and automated tools for accurate analysis. Also, a longitudinal research approach could be used as it could investigate the long-term impact of exposure to conceptual associations on learners' comprehension and cognitive development, evaluating the effectiveness of integrating such associations into language instruction. Learner-based data using specifically designed texts based on particular conceptual association clusters may provide more insights towards learner’s comprehension performance. Finally, comparing conceptual associations across CEFR levels could reveal how learners process abstract ideas at different proficiency stages, helping to design materials that progressively introduce complex relationships as learners progress through the CEFR levels.

Conclusion

This research provides valuable insights for English language studies, the psychology of language, and material design within the CEFR framework, achieved through an examination of B2 texts designed for EFL learners, specifically focusing on lexical cohesion. Utilizing a network-based approach by Yang and González-Bailón (2017) combined with the semantic taxonomy developed by Towns (2021), the study explored the interplay of semantic relationships and their impact on textual coherence. The findings reveal that B2 texts predominantly rely on logical relations, such as synonymy, antonymy, and part-whole relationships, to establish cohesion. While these straightforward connections support intermediate learners' comprehension, the study highlights a notable underrepresentation of conceptual associations, particularly within the entities category. This imbalance raises concerns about the adequacy of B2 texts in preparing learners for the cognitive demands of C1-level content, which requires engaging with more abstract and interconnected concepts.

The study further underscores the role of topic complexity in shaping the presence of conceptual associations, with more detailed and specific topics fostering a richer network of conceptual links. While the emphasis on logical relations at the B2 level supports pedagogical goals by fostering clarity and accessibility, the limited inclusion of conceptual associations points to a missed opportunity to cultivate critical thinking and higher-order comprehension skills. This research advocates for a rebalancing in text design to advance learners' ability to navigate complex discourse at the B2 level and beyond. Incorporating more conceptual associations that mirror the interconnectedness of ideas could enhance textual cohesion and better equip learners for advanced communication tasks.

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