KARADENİZ TECHNICAL UNIVERSITY * THE INSTITUTE OF SOCIAL SCIENCES

DEPARTMENT OF WESTERN LANGUAGES AND LITERATURE

MASTER’S PROGRAM IN APPLIED LINGUISTICS

CURATION AND DEVELOPMENT OF DOMAIN-SPECIFIC TERMINOLOGY AND STUDY MATERIALS IN ACADEMIC ENGLISH INSTRUCTION: MARITIME TRANSPORTATION AND MANAGEMENT ENGINEERING

MASTER’S THESIS

Atlas KÖROĞLU

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TRABZON

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Supervisor: Assoc. Prof. Dr. Ali Şükrü ÖZBAY

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APPROVAL

Upon the submission of the dissertation, **Atlas KÖROĞLU** has defended the study **"Curation and Development of Domain-Specific Terminology and Study Materials in Academic English Instruction: Maritime Transportation and Management Engineering"** in partial fulfillment of the requirements for the degree of Master of Arts in Applied Linguistics at Karadeniz Technical University, and the study has been found fully adequate in scope and quality as a thesis by **unanimous / majority** on **05.09.2025.**

Committee Member		**Decision**		**Signature**
Name and Surname	**Mission**	**Accept**	**Refuse**	
Assoc. Prof. Dr. Ali Şükrü ÖZBAY	Supervisor	☐	☐	
Prof. Dr. Özkan KIRMIZI	Member	☐	☐	
Asst. Prof. Dr. Muhammed BAYDERE	Member	☐	☐	

Approval of the Graduate School of Social Sciences.

Prof. Dr. Haydar AKYAZI
Director

DECLARATION OF ORIGINALITY

I, **Atlas KÖROĞLU**, hereby confirm and certify that;

- I am the sole author of this work and I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution,
- this work contains no material that has been submitted or accepted for a degree or diploma in any other university or institution,
- all data and findings in the work have not been falsified or embellished,
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Date 05.09.2025

ACKNOWLEDGEMENT

I am deeply grateful to my advisor, Assoc. Prof. Dr. Ali Şükrü Özbay, whose guidance and encouragement have been a constant source of support throughout this thesis journey. His insightful feedback and understanding attitude made this process not only possible but also meaningful. I truly appreciate the time and effort he dedicated to helping me grow both academically and personally.

I also owe my sincerest thanks to my family. Their patience, support, unconditional love, and faith in me have been the foundation of my strength during this demanding period. Every step of this journey was made easier knowing they were always there, even when I could not be.

September, 2025 Atlas KÖROĞLU

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ÖZET

Alana-özgü terim öğretimi, güncel derlem temelli çalışmaların da gösterdiği üzere, Özel Amaçlı İngilizce (ESP) araştırmalarında büyük öneme sahiptir. ESP'nin geniş kapsamı içinde yer alan denizcilik İngilizcesi, ülkeler arası ticaretin kolaylaştırılmasında kritik bir rol oynar ve ülkelerin ekonomik yapıları açısından inkâr edilemez bir konuma sahiptir. Bu durum, denizcilik İngilizcesinin hem sınıf içinde hem de sınıf dışında açık şekilde öğretilmesini gerekli kılmaktadır. Denizcilik alanında çalışanlar için alana özgü kelimeleri, kelime gruplarını ve deyimsel kalıpları bilmek, diğer ülkelerle açık bir iletişim kurabilmek ve bu alanda kullanılan kelimelerin büyük kısmının İngilizce olması nedeniyle son derece önemlidir. Bu çalışmanın amacı, Deniz Ulaştırma ve İşletme Mühendisliği öğrencileri için alan-özgü bir kelime listesi hazırlamak, bu kelimeleri içeren çalışma materyalleri ve özel olarak tasarlanmış etkinlikler geliştirmek ve bu kelimelerin yalnızca ezberlenmesini değil, anlamlı bağlamlar içinde öğrenilmesini sağlamaktır. Teknik kelime listesinin oluşturulması amacıyla 410.000 tokenlik bir derlem (MAR-ENGCORP) hazırlanmış ve Sketch Engine yazılımıyla analiz edilmiştir. Elde edilen en sık geçen 450 kelime, alandaki iki önemli kelime listesi olan Akademik Kelime Listesi (AWL) ve Genel Hizmet Listesi (GSL) ile karşılaştırılmış ve bu listelerde yer alan yaygın kelimeler elenmiştir. Geriye kalan 86 kelime, iki farklı yapay zeka aracı (ChatGPT —4o-mini modeli— ve Microsoft Copilot) aracılığıyla değerlendirilmiş ve en uygun olanlar seçilerek 80 kelimelik nihai liste oluşturulmuştur. Bu kelimeleri içeren bir ön test 75 öğrenciye uygulanmıştır. Test sonuçlarına göre, öğrencilerin çoğunluğu tarafından bilinen kelimeler listeden çıkarılmış ve kalan 70 kelime çalışma materyallerinin oluşturulmasında kullanılmıştır. Materyaller dört hafta boyunca öğrencilere uygulanmış ve dört haftanın sonunda bir son test uygulanarak materyallerin öğrencilerin öğrenmesine ne derece katkıda bulunduğu hesaplanmıştır. Bunun yanı sıra teknik kelime listesi ve çalışma materyalleri hakkında katılımcıların görüşlerini toplamak amacıyla çevrim içi bir anket paylaşılmıştır. Çalışma materyallerinin uygulanmasının ardından gözlemlenen etkiler teknik kelime öğreniminde belirgin bir gelişim olduğunu ortaya koymuştur. Katılımcılardan alınan olumlu geri dönüşler bu bulguyu desteklemektedir.

Anahtar Kelimeler: Teknik Kelime, Özel Amaçlı İngilizce, Denizcilik İngilizcesi, Derlem Dilbilim, Yapay Zeka

ABSTRACT

Field-specific terminology teaching, as emphasized by current corpus-driven studies, holds great importance in English for Specific Purposes (ESP) research. Within the wide scope of ESP, maritime English plays a critical role in facilitating trade between countries and holds an indisputable place in the economic structures of nations. This makes it essential to teach it explicitly both inside and outside the classroom. The need-to-know field-specific words, word combinations, and phraseological frames is evident among maritime professionals—not only for effective international communication but also because a large portion of the vocabulary used in the field is in English. The aim of the current study is to prepare a field-specific vocabulary list to be used by Maritime Transportation and Management Engineering students, and to develop study materials and specially designed exercises to help students learn these vocabulary items through meaningful contextual patterns rather than simple memorization. To compile the technical word list, a corpus (MAR-ENGCORP) consisting of 410,000 tokens was created and analyzed using Sketch Engine software. From this, the 450 most frequent words were selected. These words were then compared against two widely recognized lists—the Academic Word List (AWL) and the General Service List (GSL)—to exclude commonly known words. The remaining set of 86 words was evaluated using two AI tools (ChatGPT —4o-mini— and Microsoft Copilot) to identify the most relevant items. In the end, a list of 80 field-specific words was finalized. A pre-test containing these words was administered to 75 students. Based on the results, words that were already known by the majority were removed, leaving 70 words for the instructional materials. These materials were implemented with the participants over four weeks, and at the end of this process, a post test was administered to evaluate the extent to which the materials contributed to the participants' learning. In addition, an online questionnaire was shared in order to collect the opinions of the participants about the technical vocabulary list and the study materials. The effects observed following the implementation of the study materials revealed a significant improvement in technical vocabulary learning. The positive feedback received from the participants supports this finding.

Keywords: Technical Vocabulary, English for Specific Purposes, Maritime English, Corpus Linguistics, Artificial Intelligence

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LIST OF ABBREVIATIONS

AI	: Artificial Intelligence
AWL	: the Academic Word List
ChatGPT	: Chat Generative Pre-Trained Transformer
EAP	: English for Academic Purposes
EFL	: English as a Foreign Language
EOP	: English for Occupational Purposes
ESL	: English as a Second Language
ESP	: English for Specific Purposes
GSL	: the General Service List
MARENG-CORP	: Maritime Engineering Corpus
NGSL	: the New General Service List

INTRODUCTION

English, also referred to as the global language (Rao, 2019; Melitz, 2016), became the dominant language used as a medium of communication among seafarers across the world as a result of the role England played in global maritime activities in the Age of Exploration (O'Hara, 2009). As a language that has been playing a pivotal role in global communication for over 300 years (Hjarvard, 2004), it has become a necessity to learn it. Consequently, in 1977, the use of English as a lingua franca for communication among seafarers was formalized by the International Maritime Organization (IMO) General Assembly (Bocanegra-Valle, 2013).

Vocabulary acquisition, because of the vital role it plays in learners' both receptive (Corson, 1997; Nation & Nation, 2001) and expressive (Karakoç & Köse, 2017; Liu, 2021) language skills, is a key element for the learners of any foreign language. The importance of vocabulary, thus, has motivated researchers to focus on teaching it with the help of corpora. Still, despite their usefulness, selecting which word to teach and determining the appropriate order has been proven to be a challenge, as there is no consensus on what to teach and how to teach it (Vongpumivitch, et al., 2009). To tackle this predicament, researchers, with the assistance of corpus-based methods, started to create word lists that provided language learners with the most essential vocabulary of the language they are learning. These word lists could be sorted according to word frequency, or in any way that would best serve the learners' interests.

Corpora, a concept introduced to the field of education more than three decades ago (Sinclair and Renouf, 1988), refers to the collection of large amounts of data gathered from materials that represent the field on which the study focuses. As a corpus is expected to have large amounts of data, corpus-analyzing software holds a prominent position, because only through these tools can the corpus data be analyzed and sorted (Hunston, 2002). With the popularity of the use of corpora in language teaching growing, the number of corpus-compiling and analyzing software increased too. Among them, some of the most widely used ones are WordSmith Tools, Sketch Engine, and AntConc. With such tools, large corpus data can be compiled, analyzed, and sorted to serve the needs of the researcher in creating specialized word lists. Among these, Sketch Engine, a free online software that can be utilized in the analysis of the compiled corpus data, holds a prominent place thanks to the various features it offers such as word list creation, concordance analysis, and word sketch difference from which users can benefit. Among these features, the most relevant to the present study is the "Word lists" section, where the users are provided with a vocabulary list sorted according to the frequency of the words (also known as tokens) appearing in the corpus data.

CHAPTER ONE

1. FRAMEWORK OF THE STUDY

1.1. Background of the Study

In literature, West's (1953) General Service List (GSL) of the most commonly used vocabulary in the English language, which remains influential even today, has pioneered the creation of other word lists, such as Coxhead's Academic Word List (2000), which contains vocabulary specifically designed for academic purposes, and Browne et al.'s (2013) the New General Service List, an updated version of the GSL, that are among the best-known word lists. Still, however successful these lists of vocabulary were at helping learners acquire the required vocabulary to increase their receptive skills, as backed up by Hyland and Tse (2007), there was still a need for word lists that contained vocabulary specific to different branches of study.

Since West's (1953) General Service List, word lists have been grouped into three categories: general academic word lists, discipline-specific word lists, and subject-specific word lists (Dang, 2020). General academic word lists contain words commonly used across different academic fields and aim to help students understand academic texts meanwhile discipline-specific word lists consist of words that are common between different areas of study, and subject-specific word lists, also known as technical word lists, contain the most specialized lists of vocabulary unique to a field (Nation, 2005), and are used in various disciplines. According to Hyland and Tse (2007), among the other categories, technical vocabulary is the most prominent, and therefore, ought to be prioritized in language classrooms. For this reason, discipline-specific word lists, to fulfill the need for field-specific word lists, for fields such as engineering, nursing, plumbing, zoology, and linguistics have been created (e.g. Mudraya, 2006; Mukundan & Jin, 2012; Coxhead & Demecheleer, 2018; Kruawong & Phoocharoensil, 2018).

The significance of vocabulary in English education is indisputable, and there is a great body of ever-growing research data that draws attention to the success of needs-specific word lists. However, even though research in this area is extensive, studies focusing on the curation of word lists specifically for the field of Maritime Transportation and Management Engineering are non-existent. Thus, in the current study, the aim is to create a technical word list that will be of use to Maritime Transportation and Management Engineering students in both their studies and professional lives.

Corpus data specifically compiled for the current study was gathered from prestigious articles written by experts in the field in question. In such articles, the use of vocabulary is not only professional but also closely related to the field. The computer software utilized for both the compilation and analysis of the raw research data was Sketch Engine. The vocabulary list, sorted by word frequency, was edited, and the first 450 words were selected. These words were, later on, cross-checked against both the AWL and the GSL. The words that were already present in these lists were eliminated. In the next step, words deemed non-technical were removed with the help of two AI Language Models (ChatGPT —4o-mini— and Microsoft Copilot). The remaining vocabulary, which was reviewed once more by a linguistic expert and a field expert —to confirm the reliability and validity of the final form of the list— was used to create a pre-test and was administered to participants to ascertain the ones that were known by a majority (75%).

Following this process, the words that the majority of the participants were unfamiliar with were taught to them by the researcher using specifically designed study materials. At the end of this four-week process, participants were given a post-test to assess the effectiveness of the study materials. The results of the pre-test and post-test were then analyzed using SPSS, a piece of software specifically designed for the social sciences and utilized for data analysis purposes.

1.2. Statement of the Problem

English has been the lingua franca for communication among seafarers since 1977 (Bocanegra-Valle, 2013). The language has played a major role in the lives of mariners ever since. Being responsible for almost all shipments around the world (Alderton & Winchester, 2002), the maritime industry has become central to global trade. With that, the necessity for a common language in which seafarers can communicate has grown as well. The role English plays is so prominent that, as stated by Mikulicic et al. (2023), miscommunication resulting from seafarers' lack of English proficiency has been proven to be the key factor behind the majority of work-related accidents.

There is ample research in the literature to prove that the English education maritime students receive fails to meet their communicative needs, which, in turn, gives rise to a plethora of problems later in their professional lives (Dirgeyasa, 2018; Yercan, 2005; Saray et al., 2021). The main cause of these problems is, as discussed in the previous paragraphs, a lack of vocabulary knowledge, which consequently cripples their receptive language skills.

Despite research evidence pointing to the importance of vocabulary in English learning and the English-related challenges nautical students face, there is no corpus-based study that prioritizes the creation of technical vocabulary lists and study materials tailored to the needs of Maritime Transportation and Management Engineering students. Even though there have been a number of studies carried out within the existing body of research on the field under consideration, they mainly focus on the use of metaphors in Maritime English (Xu et al., 2023; Wu & Cai, 2016; Isserlis, 2014).

When the importance of vocabulary acquisition in the learning of the English language, and the needs of the nautical students to learn English are considered, the lack of studies on this specific topic necessitates initial investigation to fill the critical gap.

1.3. Purpose of the Study

For learners whose goal is to learn English for a specific purpose, technical vocabulary is a matter of great importance (Chung & Nation, 2004). Such vocabulary remains a key concern in the lives of EFL learners. It is of great importance in helping learners understand the information they receive in their target language. Notwithstanding the crucial role English plays in the field, Schriever (2008), who viewed Maritime English as a means to ensure safety at sea, drawing from examples taken from real-life scenarios, where the lack of proper communication between the bridge and the coast guard caused some grave consequences, concludes that the communication errors deriving from a lack of vocabulary knowledge in English can end up putting the seafarers at risk. Additionally, miscommunication is known to be the root cause of a number of accidents at sea (John et al., 2013). Indeed, the main cause of a predominant number of work-related accidents in maritime professions is, as Mikulicic et al. (2023) state, a lack of proper communication or misunderstanding due to the lack of vocabulary knowledge among seafarers.

The current study has three main objectives. First, it aims to create a list containing technical vocabulary to serve the language needs of Maritime Transportation and Management Engineering students. The words in this list are drawn from a purposely designed corpus (MAR-ENGCORP), compiled from highly prestigious articles published in the field of Maritime Transportation and Management Engineering. High-frequency words are cross-checked against both the AWL and the GSL, and the words that do not exist in either list are fed into two AI language models, ChatGPT and Microsoft Copilot, to determine the strictly technical ones. This process results in a word list that is narrowed down to a more restricted list, which would make it more useful for learners. Subsequently, it is aimed to curate learning materials with the help of ChatGPT that will be handed to them for four consecutive weeks, with which the students will not only learn the technical vocabulary but also be provided with contextual examples where the vocabulary is illustrated in its usage. Finally, through the post-test administered to the participants at the end of the four-week process, it is intended to measure the effectiveness of the study materials. Additionally, the participants' opinions about the technical word list and the study materials were gathered through an online questionnaire.

1.4. Research Questions

The current study seeks to find answers to the following questions:

1. What is the commonly used vocabulary in Maritime Transportation and Management Engineering research articles?

2. To what extent do customized-study materials influence students' vocabulary learning outcomes?
3. Which vocabulary items showed the greatest and least improvement from pre-test to post-test, and what might explain these differences in learnability?
4. How do participants perceive the usefulness of the study materials and word list in learning technical vocabulary?

1.5. Significance of the Study

The present research is important in two ways;

a) As there has not been any research regarding the creation of a word list for the Maritime Transportation and Management Engineering department, this study presents the first technical word list specifically designed for Maritime Transportation and Management students.
b) It contributes to the field by introducing tailored study materials where the learners will get the opportunity to see the vocabulary they learn in its authentic context.

1.6. Organization of the Thesis

Chapter 1, Introduction: This chapter provides context for the selected topic while outlining the goal and importance of the research.

Chapter 2, Literature Review: This chapter reviews the literature in depth, defines key terms and presents the gap in the literature.

Chapter 3, Methodology: This chapter describes the research process, research design, and the instruments used in collecting data thoroughly.

Chapter 4, Findings and Discussion: This chapter deals with qualitative and quantitative data analyses.

Chapter 5, Conclusion and Recommendations: The conclusion is discussed in this chapter, which also highlights the thesis' importance and contribution to the field in question. It also discusses the findings' limits, consequences, and recommendations for additional research.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Introduction

In the current chapter, the necessary background data for the study's comprehension is provided in detail. First, the literature specific to English for Specific Purposes (ESP) is reviewed. After reviewing the fundamental function of ESP in language instruction, the chapter delves into corpus-based methods that guide language teaching. Subsequent to that, subject-specific word lists are covered, which are followed by earlier studies in the literature on their creation and use in specialised fields. Thereafter, the topic of how artificial intelligence techniques can be utilised to enhance vocabulary-focused training in language classrooms is explored. At the final stage of the chapter, a gap in the existing research is identified, which emphasises the need and justification for the current investigation.

2.2. English for Specific Purposes (ESP)

English for Specific Purposes, also defined as a research field concerned with technical or field-specific vocabulary (Coxhead, 2017), has been around for over 50 years (Ramirez, 2015). What sets ESP apart from general vocabulary teaching is that, in its nature, ESP study focuses on the purpose-driven use of the target language (Hyland, 2022). The need for ESP, as suggested by Hutchinson and Waters (1987), arose with English becoming the lingua franca, and thus, practitioners or students of specific branches wanting to learn adequate language skills to cater to their needs. Following the definition made by Dudley-Evans and St. John (1998), ESP can be defined under two characteristics, which are absolute characteristics and variable characteristics.

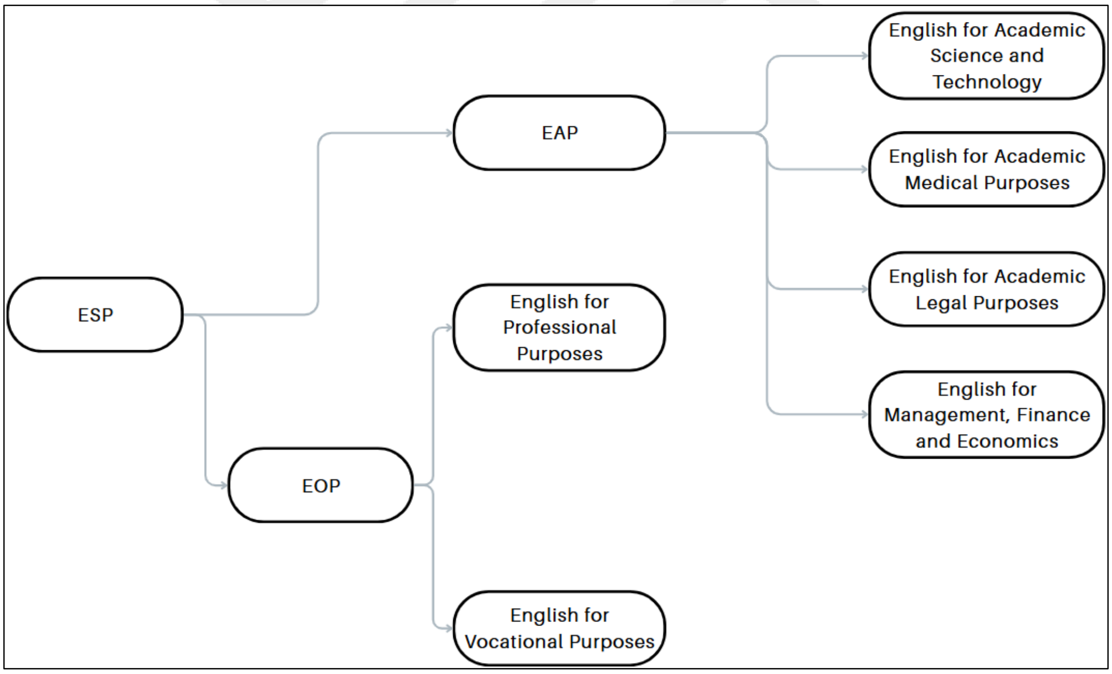
In Dudley-Evans and St. John’s (1998) definition, the absolute characteristics of ESP use the methodologies and practices of the discipline they serve, are tailored to learners’ individual needs, and focus on the language, skills, discourse, and genres relevant to these activities.

The following criteria may be included in the variable characteristics of ESP:

It may be related to or tailored for particular fields of study; it may employ a different teaching style than General English in certain contexts; and it is probably intended for adult learners, either in a postsecondary setting or in a professional setting. Although secondary school children could utilize it, it is often intended for intermediate or advanced learners. Although it can be used with beginners, the majority of ESP courses presume a basic understanding of the language system (Dudley-Evans & St. John, 1998).

Dudley-Evans and St. John (1998) also divide ESP into subcategories, where it acts as an umbrella term that branches out into varied professional domains, as shown in Figure 1. The two main subdivisions are English for Academic Purposes (EAP) and English for Occupational Purposes (EOP). The main difference between these two branches of ESP is that EAP focuses on practices that are mainly for academic purposes at the tertiary level of education, and aims to aid students with their academic purposes where they use English as the medium language in their field of study (Gillet, 2022), while EOP refers to the teaching of English that is mainly related to the profession-specific use of the language the learner would need in a professional setting or work environment (Koester, 2013).

Figure 1: ESP Classification by Professional Area



Source: Dudley-Evans & St. John, 1998: 6.

In the course of preparing ESP vocabulary lists, assessing the target needs of the learners should be the initial step, as it is of utmost importance to conduct these assessments because of the crucial differences that could emerge in the preparation of the vocabulary lists depending on the learner's field of study, level of education, or place of residence (Hyland, 2006). This technique of specializing vocabulary for the learners' needs was introduced to the field by Swales (1990) under the name of "genre analysis". In ESP, genre analysis plays an important role in relation to language learning

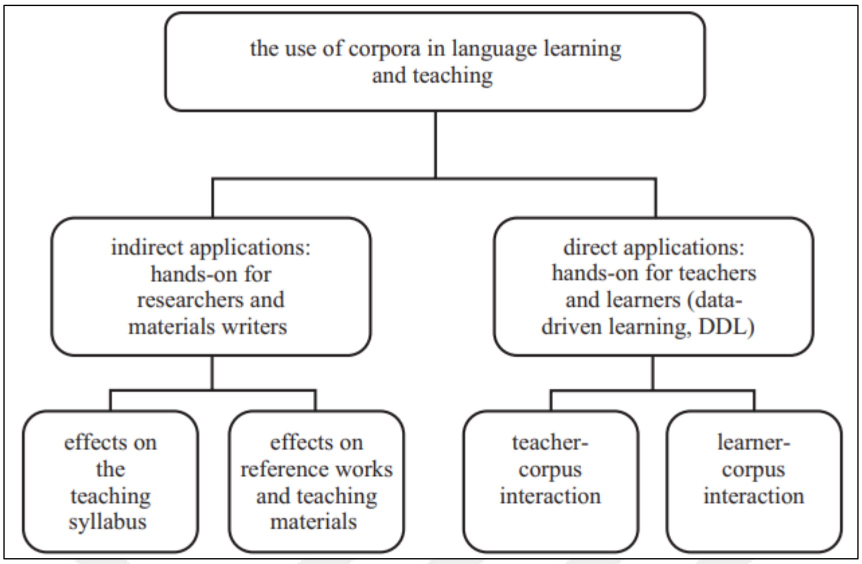
(Cheng, 2019). It "offers a system of analysis which allows observations to be made on the repeated communicative functions found in genres and the linguistic exponents of these functions" (Brett, 1994, p. 47). In this regard, corpus, which will be discussed in its own section later in the paper, is a well-known tool to discover the distinctive aspects of a genre (Flowerdew, 2005; Dong & Lu, 2020). Through the scrutiny of a specific genre, corpus can provide learners with the linguistic structures that are present in the language and are repeated consistently. These structures, which are obtained through an analysis of the corpus, can later be used to prepare study materials for the students to aid them in a variety of contexts such as their academic writing courses (Candarli, 2020).

The necessity and salience of ESP research are incontrovertible. ESP, albeit a concept that has been around for over 50 years, still continues to be relevant and is revered in the field of Applied Linguistics. Although the existing body of research in this field is of a substantial amount, there is still room for subsequent research, such as the creation of genre-specific vocabulary lists with the use of corpora, which will be discussed in detail in the following section.

2.3. Corpus Based Approaches to Language Teaching

Corpus is a concept that can be simply defined as the compilation of data collected from materials that represent the specific field in question (Francis, 1982; Sinclair, 1991). Two of the earliest names who led to the integration of corpus in language education and the development of approaches that were meant to guide strategies for teaching were Sinclair and Renouf (1988). The corpus-based approach to language teaching has not only defied the strains of time by gaining more recognition as time went by, but also transcended to almost every linguistic subfields (Xiao, 2009; Biber, Conrad & Reppen, 1998). As seen in Figure 2, when it comes to the use of corpus in a classroom setting for pedagogical purposes, there appears to be two main sub-titles, which are the indirect, and direct applications of corpus (Römer, 2008; Leech, 1997).

Figure 2: Applications of Corpora in Language Teaching



Source: Römer, 2008: 113.

2.4. Direct Application of Corpus (Data Driven Learning)

Data-driven learning (DDL), a term first used by Johns (1998) over 30 years ago, can simply be described as a teaching system whose focus is the corpus (Lewandowska, 2014). It is a student-oriented method which allows students to be autonomous while learning the target language by letting them analyze a collection of authentic texts to find the recurring patterns in it (Talai & Fotovatnia, 2012). In Johns' (1998) words, DDL makes "every student a Sherlock Holmes" (p. 101). The thrill of discovering the required information itself acts as a driving factor for learners (Granger & Gilquin, 2010).

In a classroom environment, DDL can be used in two ways for students to access the data; directly or indirectly. As Huang (2014) noted, indirect (hands-off-application) is when the students are given ready-made lists prepared by their instructors, while in direct-i.e., hands-on-application, they analyze the corpora themselves to find the recurring patterns. In other words, hands-on learning happens in a more controlled environment (Smart, 2014) compared to hands-off learning where students are autonomous and more aware of the language as they have the freedom to use the corpus tools by themselves (Saeedakhtar, 2020).

However, even though DDL is an effective approach that is advantageous to learners (Granger and Gilquin, 2010), it would be important to note that it has its shortcomings. To begin with, learners will be required to learn how to use software needed to analyze the corpus data (Boulton, 2017). Boulton (2017) points out that, because the software can be hard to navigate for the learners, unless they are trained very well on it, there is a possibility for them to become fatigued because of the laborious and complex process, or to come up with incorrect "queries". On top of that, dealing with corpus can be a time-consuming process (Chang, 2014; Boulton & Tyne, 2013). One other issue is that hands-on DDL, in general, is suitable for advanced learners of the target language, which can make it impractical for classrooms with students who have elementary or intermediate English levels.

2.5. Indirect Application of Corpora

The indirect use of corpus, in Römer's (2008) words, plays an indispensable role in the content design of both study and teaching materials. When it comes to the way corpus is integrated into the classroom environment, the indirect application of corpus —regarding reasons such as requiring no experience or extra preparation on either the students' or the instructors' part, and needing no software to run it— has been favored more than the direct application (McEnery & Xiao, 2011). On top of that, compared to the direct application of corpus, where students might find it quite hard to draw astute inferences from the corpus data because of its complex structure (Sinclair, 2004), in indirect application of corpus, the data provided to them by the instructor is already scrutinized, which, in turn, reduces the chances of the students being misled. The data retrieved from a sufficiently large corpus provides the material designers with grounded content from which they can pick vocabulary to create needs-targeted word lists that would be useful for the learners of the target language in their learning journey (Dang, 2020).

The structure of the corpus data, when analyzed with the help of a corpus analysis tool, grants analysts the freedom to access the exact information they seek without having to analyze the entire body of data linearly until they find what they need, because it "…is stored in such a way that it can be analysed non-linearly, and both quantitatively and qualitatively" (Hunston, 2002 p. 2). As stated above, computer software used to analyze corpora plays a crucial role in the appropriate use of data because, as highlighted by Hunston (2002), without the compiler, corpus data is just a pile of text. In fact, the use of such computer software is so important that Leech (1992, p. 105) goes as far as calling it the "new master" of corpus linguistics. Some examples of software for compiling and analyzing corpus data that can be used for preparing vocabulary lists include Sketch Engine (Kilgarriff et al. 2008) and AntConc (Anthony, 2005), to name but a few. With the help of such tools, word lists that are arranged either alphabetically or in order of frequency can be created (O'Keeffe et al., 2007). In the literature, there are three types of specialized word lists (Dang, 2020). See Table 1.

Table 1: Types of Specialized Word Lists

Type	Description
General Academic Word Lists	Contains common vocabulary among different branches of the academia Has the purpose of making the learners understand academic content in the target language Coxhead (2000) The Academic Word List (AWL) with 3,500,000 tokens

Table 1: (Continued)

Discipline Specific Word Lists	**Is concerned with the shared vocabulary between different fields of study.** **Draws attention to the connection between similar disciplines.**
Subject Specific Word Lists	Also called as "technical-vocabulary" (Dang, 2020, p 4). Contains the most specific lists of vocabulary Is used commonly in fields such as linguistics, medicine, chemistry and engineering.

Source: Dang, 2020.

2.6. Subject Specific Word Lists (Technical Word lists)

Subject-specific, or in other words technical word lists, as can also be seen in Table 1, are lists that contain words that pertain to a specific field of study (Nation, 2005). As supported by Hyland and Tse (2007), it is imperative that learners be encouraged to learn subject-specific vocabulary. The vocabulary that could be considered suitable enough to be included in a technical word list can be determined by following Chung and Nation's (2004) rating scale. According to this scale, there are four key criteria to consider in the process of choosing words for a technical word list:

a. Vocabulary that is not related to the field in question.
b. Vocabulary whose relation to the field in question is minimal.
c. Vocabulary whose relation to the field in question is strong, but might also be encountered in different disciplines.
d. Vocabulary which is specific to the boundaries of the field of study, and is unlikely to occur in other fields.

According to the scale, for a word to be considered technical, it should meet the third or the fourth criteria as the first and second are not classified as technical vocabulary. In the literature, there have been numerous studies that aimed at creating technical word lists tailored to different fields of study.

2.6.1. Research on Technical Word Lists

Chen and Lei (2019) designed a study to develop a technical word list for the subfields of Computer Science (TWLRACS). The researchers compiled a 10,45-million-word corpus (CRACS) drawn from 1,045 research articles to identify the frequently occurring technical words across 10 disciplines under the umbrella of Computer Science such as artificial intelligence and pattern recognition, computer science theory, and computer graphics and multimedia. After analyzing the corpus, the list of the most frequently occurring words that were in common in at least 5 of the subdisciplines were selected which, later, were scrutinized for further refinement by two experts to exclude the vocabulary items that were not related to the field. Following this process, the resulting 1,262-word types were compared to both the GSL and the AWL, and any word that occurred on either list was removed. The remaining 769 words were used to create the TWLRACS.

In the field of finance, Tongpoon-Patanasorn (2018) conducted a quantitative study to create a high-frequency technical word list that would provide both educators and learners in the finance department with a targeted vocabulary resource. The corpus for the study (KKU BE-Finance Corpus) with a total of 2 million running words compiled from textbooks and journals, was compared against a reference corpus (BAWE) to filter out common words that occurred frequently in both corpora. Following this process, the remaining 3,002 words were inspected by two experts, who rated a total of 979 of them as strictly technical. Finally, after grouping the words into word families, 569 words were curated into the technical word list for finance.

One other study focusing on the curation of technical vocabulary was conducted by Coxhead and Demecheleer (2018), which investigates the technical words belonging to the field of plumbing so as to be used by trainee plumbers. In their corpus-based research, Coxhead and Demecheleer (2018) compiled two separate corpora: one containing written data retrieved from sources such as instruction manuals and textbooks, comprising 565,881 tokens, and one containing spoken data that came to a total of 133,093 tokens, which they recorded in plumbing classes. The word list they created covered 32.17% of the written corpus and 11.14% of the spoken corpus, the 1465 technical words were then categorized into 14 sub-lists.

Similarly, in a study implemented for the purpose of serving the needs of nursing educators in designing their ESP curriculum, Mukundan and Jin (2012) aimed to create a Nursing Technical Word List (NEWL) using corpus data containing 3,490,417 words compiled from nursing textbooks. The researchers followed a strategy similar to that of Tongpoon-Patanasorn's research (2018), in which they compared their corpus (NEC) against the BNC and selected words that appeared frequently in NEC as candidates for NEWL, which were 2,476 words in total. Then, these words were crosschecked against the AWL and the GSL to further refine the word list. As a final step, Mukundan and Jin (2012) had their word list checked by three experts to filter out non-technical words. The resulting technical word list contained 969 words, with a lexical coverage of 9.5%.

A similar study mainly focused on creating a field-specific word list of high frequency vocabulary for medical students was conducted by Hsu (2013). By compiling a 15 million-word corpus that contained 155 medical coursebooks across 31 subbranches of the field, Hsu (2013), thus, created the Medical Textbook Corpus (MTC), which he later compared against the BNC to exclude the words in the MTC that appeared among the top 3,000 most frequent words of the BNC. The remaining vocabulary was further processed by including only the words that both appeared at least 863 times in the MTC and occurred in no fewer than 16 medical sub-branches. With a lexical coverage rate of 10.72%, Hsu’s (2013) final Medical Word List (MWL), which consisted of 595 words, is aimed to facilitate medical students’ comprehension of medical texts.

Another study aiming to create a technical word list for medical students’ use was done by Fraser et al. (2025). In their research, the researchers followed a three-pronged approach: needs analysis followed by corpus analysis, and material development. Unlike Hsu’s (2013) study, however, in the Medical English Word List (MEWL), created by Fraser et al. (2025), the authors did not strictly rely on corpus frequency while selecting vocabulary. Instead, the researchers developed 14 course units that included doctor-patient and doctor-doctor discourse, and organized them according to body systems. An Excel-based list including approximately 1,700 items was created by manually extracting key terms from these units. The study team created two reference corpora from Harrison's Principles of Internal Medicine and Gray's Anatomy for Students to identify any gaps and make sure everything was covered. These corpora were used as validation tools to verify frequency, technicality, and distribution across authentic medical texts rather than filtering words statistically. The final list had 170-item word-parts in addition to single and multiword entries. The MEWL was created to be pedagogically relevant to the field and thoroughly integrated into contextualized materials.

Le and Miller (2025), in a corpus and semantics-based study, had the objective of developing lexical materials to help medical students understand semi-technical medical terms. The base of the study was Hsu’s (2013) MWL, from which the researchers identified 302 words that had multiple meanings to focus on. During the word selection process, there were three criteria to be taken into consideration: semantic complexity, part of speech variety, and pedagogical relevance. Le and Miller (2025), instead of creating their own research corpus, relied on two existing corpora: English Webb 2020 —with 43,125,207,462 running words— and the Medical Eb Corpus —containing 42,054,011 tokens. These corpora were used to check how often the vocabulary they extracted from the MWL appeared on them, and how their meanings changed across general and medical contexts. Following this analysis, they categorized each word by frequency and technicality level. The vocabulary items, then, were presented through a technique called “Lexical Constellation”, which showed the core meanings of each word and its semantically related forms in surrounding clusters. The learning material, SemiMed, was piloted with 18 upper-intermediate medical students through role-play scenarios. The results indicated that the learners of the study found SemiMed to be much more helpful than traditional dictionaries and recources.

In another corpus-based study, Kruawong and Phoocharoensil (2018) sought to develop a zoology word list to serve the needs of students and educators. After compiling the Zoology Research Articles Corpus (ZRAC), containing 1,530,384 words from 268 research articles in the field of Zoology, words were selected based on two criteria: (1) the words had to appear more than 50 times in the corpus, and (2) they had to be present in at least six articles that were used in the compilation of the research data. 504 selected words were later submitted to seven zoology experts for further filtering. The final list contained 286 words, accounting for 9.5% of the overall corpus coverage.

Coxhead et al. (2016), in a corpus-based study, aimed to create a technical word list to be used by carpentry trainees with the purpose of helping lessen the challenges faced by the practitioners of the field regarding technical vocabulary. Using corpus data consisting of 300,594 words, compiled from instruction manuals, workbooks, and unit standards used in Carpentry programs at levels 3 and 4, the researchers followed a five-step refinement approach to determine strictly technical vocabulary. The first step was to compare the corpus against Nation's BNC/COCA word lists to eliminate general vocabulary and retain the remaining words with specialized meanings in the field. In the second step, words that appeared at least 10 times in the Carpentry corpus were selected, and those not occurring in any of the lists except the carpentry corpus were refined; and the words that appeared at least 4 times in the corpus were retained. Finally, the resulting word list was handed to carpentry educators to classify the words as technical or non-technical which led to the creation of the Carpentry Pedagogical Word List, with a coverage of 5.26% words and containing 1,424 vocabulary items. The word list, then, was divided into sublists based on the frequency of the words to make it easier to be learned.

Another research study that adopts a lexical profiling approach in creating technical word lists is Laosrirattanachai and Laosrirattanachai (2021) who, by compiling the Thai Tourist Guide Corpus (TTGC) with 653,196 tokens, aimed to construct a technical word list to be used by Thai tourist guides. The TTGC was compiled from an official website dedicated to tourism, describing tourist attractions in Thailand. The corpus was cross-checked against three different word lists —GSL, AWL, and TBWL (Tourism Business Word List)— and any word appearing in any of those lists were eliminated. The remaining vocabulary was checked against the BNC and COCA for the purpose of identifying the words that appeared more than 23,000 times in either list, and excluding those that did not from the final list. The final version of the list was examined by five tourist guides to be rated using Chung & Nation's (2004) four-point scale of technicality to select the most relevant vocabulary items, leading to the creation of the Thai Tourist Guide Word List, which contained 391 words and covered approximately 20% coverage of the overall corpus.

In the field of applied linguistics, Khani and Tazik (2013) aimed to create a field-specific word list to aid both practitioners and learners of the field. The research data was collected from 240 research articles coming to a total of 1,553,450 tokens. In order to fulfill the aim of refining the vocabulary, the researchers adopted a two-step criterion: (1) they selected only words that appeared more than 50 times in the research corpus, and (2) words that appeared more than four times in at least six articles were included in the corpus. The researchers identified 773 words in total to construct the word list, which achieved 12.48% coverage.

Table 2: Studies Conducted on the Creation of Technical Word Lists

Author(s)	Date	Title	Running Words
Chen and Lei	2019	TWLRACS (Computer Science)	10,045,000
Tongpoon-Patanasorn	2018	KKU BE-Finance Corpus (Finance)	2,000,000
Coxhead et al	2016	Carpentry Corpus	300,594
Mukundan & Jin	2012	ENP (Nursing)	3,490,417
Hsu	2013	MTC (Medical Textbook Corpus)	15,000,000
Fraser et al.	2025	MEWL (Medical English Word List)	ND
Le & Miller	2025	English Web 2020, Medical Web Corpus	43,167,261,473
Kruawong & Phoocharoensil	2018	ZRAC (Zoology)	1,530,384
Coxhead & Demecheleer	2018	Plumbing Corpus	565,881
Laosrirattanachai & Laosrirattanachai	2021	TTGC (Tourism)	653,196
Khani & Tazik	2013	Applied Linguistics Corpus	1,553,450

2.7. Use of AI Chatbots in Language Classroom

AI chatbots can be defined as digital systems designed with the objective of achieving human-like cognitive abilities that could be utilized for various purposes, such as analytical thinking, or sorting data (Russell and Norvig, 2010; Luckin et al., 2016; Cukurova, 2024). In this thesis, AI is used to analyze language data and make evaluations about word relevance in terms of statistical and contextual patterns. In recent years, thanks to the latest advancements in Natural Language Processing and machine learning technologies (Caldarini et al., 2022), AI chatbots have had a profound impact on various fields, including pedagogy (Nyaaba & Zhai, 2024), finance, psychology, and healthcare (Luo et al., 2022; Caldarini et al., 2022). Over the past few years, the use of AI tools in classroom settings has garnered researchers' attention (Zhang et al., 2023) as students learning a foreign language, through interactions with AI chatbots, can get a chance to engage in authentic, real-life conversations (Belda-Medina & Calvo-Ferrer, 2022; Kalla et al., 2023). Consequently, there is a growing body of research aimed at assessing the impact of AI-mediated learning and teaching on the learners of a foreign language.

In a qualitative study conducted in Turkey, Yener and Selçuk (2024) investigated the influence of AI chatbots on students' use of the present perfect tense, which is a topic difficult to grasp for various reasons, such as the absence of this structure in the students' native language. The results of the research revealed that the implementation of AI had several benefits on the students' part, such as providing them with instant feedback, and helping them gain self-autonomy. It was also found that 72% of the participants showed significant progress in the accuracy of their output.

Hatmanto and Sari (2023) evaluated ChatGPT's integration into language teaching by exploring the alignment of the AI chatbot with well-grounded theoretical frameworks, including Task-Based Learning, Constructivist Learning Theory, Communicative Language Teaching, and Personalization and Differentiation. The study also aimed to identify pedagogical methods through which the AI chatbot could be used most effectively. The study emphasizes how ChatGPT might employ pedagogical methods such as group projects, role playing, Socratic dialogues, and interactive storytelling to enhance learner engagement, fluency, and customized learning experiences. The results also highlight ChatGPT's potential for differentiated training, enabling students to engage at their own level of competency while receiving immediate feedback. Hatmanto and Sari conclude their study with the implication that even though the AI chatbot provides the learners with authentic context and enhances self-directed learning, there is still a need for further investigation to evaluate its long-term effects on learners' higher-order cognitive abilities.

In a similar mixed-methods study, Wei (2023) explored the influence of AI-centered language teaching on students' learning skills, along with their motivation levels and self-autonomy. The tool used for the study was Duolingo, a language learning platform powered by AI. The participants of this study were divided into two groups: a control group (n = 30) and an experimental group (n = 30). The experimental group received AI-centered instruction while the control group was taught using traditional methods. The quantitative findings of the study showed that the control group was outperformed by the experimental group in writing, reading, and vocabulary knowledge. Apart from that, the participants of the experimental group were found to be more motivated and autonomous compared to the control group.

Troukhanova (2024), in their article, draws attention to the changing paradigms in education brought about by the introduction of AI, and the benefits of this timely shift for maritime students and instructors. The author points out that, with the help of AI tools such as grammar checkers and chatbots, students become more self-autonomous. In addition to this, a specifically tailored, practical AI chatbot called "The Maritime and Naval English Guide" allows them to experience real life scenarios through interactive role plays. Troukhanova also mentions how the utilization of such tools could both reduce the workload of the instructors and help them produce more effective materials that would meet the needs of students.

2.8. Research Gap

As seen in Table 2, several research studies have examined various fields —such as nursing, zoology, plumbing, tourism and applied linguistics to name but a few— to create subject-specific word lists for learners of these fields. However, based on the information the researcher has gathered, there has been no such study done in the field of Maritime Transportation and Management Engineering department.

With the purpose of filling the aforementioned gap, the present study set out to create a Maritime Transportation and Management Engineering corpus, through which a list of commonly occurring field-specific vocabulary would be created. In the creation of the word-list, the first step was to eliminate function words (e.g., "a," "an," "the"), which was then followed by the selection of the first 450 words in the MAR-ENGCORP. These words, then, were cross-checked against the AWL (Coxhead, 2000) and the GSL (West, 1953) to identify those that occurred in either of the lists. The words that were found in either list were excluded (Jin et al, 2013). The remaining 86 words were uploaded to ChatGPT and Co-Pilot for further assessment. Words that both chatbots identified as unrelated to the field were removed from the list, and the remaining 80 words were treated as the Maritime Transportation and Management Engineering technical word list. The final version of the list was checked by two experts; a linguist specializing in the field of ESP, and an academic working in the field, to verify that the final form of the word list was reliable and valid.

CHAPTER THREE

3. METHODOLOGY

3.1. Introduction

In the current chapter, the corpus data collection process and the development of the pre-test and post-test were discussed. Following that, the preparation process and the use of study materials were explained in detail, followed by a section explaining the participant profile. Finally, the handling and the analysis of the research data were explained.

3.2. Corpus Compilation

The research data for the current study is composed of articles related to the field of Maritime Engineering. To ensure their relevance and quality, the articles selected to elicit the corpus data were required to be in line with three criteria: their relevance to the field, their date of publication, and the quartile ranking of the journal in which they were published. Based on these criteria, 52 articles, earliest of which dates back to 2018, that are published in Q1 ranked journals and indexed in SSCI and SCI were selected to compile the research data in the creation of a technical word list.

Table 3: The Information on MAR-ENGCORP

Corpus Size	410,000 words
Number of Articles	52 articles
Subject	Maritime Transportation and Management Engineering
Text Types	Research articles related to the field in question
Language	English

Following this process, before being fed into the corpus tool, the selected articles —which were downloaded as pdf files— were converted into text files and stripped of all the tables, references, images, and figures. Next, the remaining files, which contained a total of 410,000 tokens, were used to aggregate the MAR-ENGCORP. The research data, then, was uploaded to Sketch Engine, an online corpus analysis tool which is capable of performing various tasks, one of which —that also aligns with the purposes of this study— is the creation of frequency-based word lists. As can also be seen in Figure 3, apart from arranging words based on their percentage of occurrence in the uploaded data, the software also displays the frequency information of each vocabulary item. Additionally, Sketch Engine provides its users with the KWIC function (Figure 4), which is particularly useful when viewing the word in its authentic context is a necessity.

Figure 3: Word Sketch Function in Sketch Engine

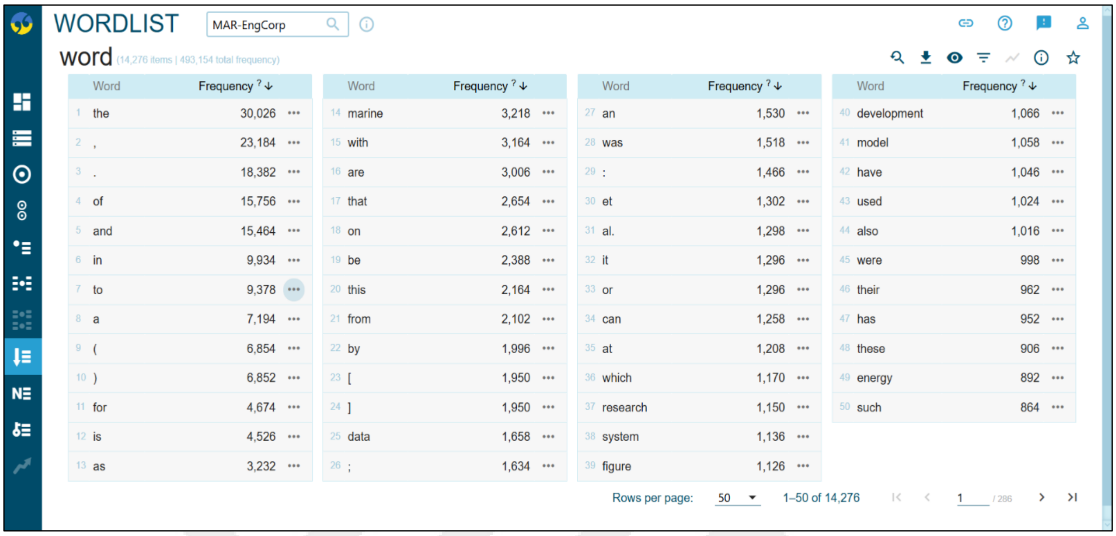


Figure 4: KWIC Function in Sketch Engine

3.3. Pre-test and Post-Test

After MAR-ENGCORP was analyzed using Sketch Engine, the words that were sorted in terms of their frequency were extracted and after being cross checked against both the AWL and GSL. Words that were not included in either word list were used to create the technical word list. Following that, the word list was uploaded to ChatGPT (4o-mini model) and Microsoft Copilot, and the chatbots were asked to evaluate the words and select the ones that were most relevant to the field. These chatbots were chosen for two reasons: one of them is their extensive training on large, diverse datasets, and the other is significant industry funding they receive in terms of development, which makes them reliable tools for language related tasks. Six words deemed as irrelevant to the field of Maritime Transportation and Management Engineering by both chatbots were removed from the list (see Appendix 4), and the remaining 80 vocabulary items were used to construct the pre-test. Subsequently, the final version of the technical vocabulary list was checked by a linguist and an academic in the field one last time.

Table 4: Word Selection Process

Step	Description
Corpus Analysis	MAR-ENGCORP is analysed using Sketch Engine, sorting words by frequency.
Cross Checking	Words compared against AWL and GSL; words not in either of these lists selected for the technical word list.
Chatbot Validation	Word list uploaded to ChatGPT and Microsoft Copilot; chatbots reviewed and filtered words for relevance.
Word Removal	Six words deemed irrelevant to Maritime Transportation and Management Engineering were removed.
Pre-test Creation	Final list of 80 vocabulary items used to create the pre-test.
Expert Review	Final version of the technical vocabulary list verified by a field expert and an expert in linguistics.

When the pre-test was administered to the participants of the study, they were asked to write the Turkish equivalents of the words on the test. In implementing the preliminary test, the researcher had two objectives, first of which was to identify the words that were already known by the majority of participants; these words would be removed from the vocabulary intended for use in the preparation of study materials. The second objective was to measure the effectiveness of the study materials by comparing the pre-test and post-test results obtained from the participants. Appendix 5 shows a sample of the pre-test. After the administration of the pre-test, the words answered correctly by at least 75% of the participants were extracted, and the remaining 70 vocabulary items were used in the creation of the post-test (Appendix 6).

3.4. Study Materials

In the present study, while determining the exact number of words that should be included in the pre-test, the researcher took Webb and Nation’s (2017) explanation into account, which states that there is no consensus on how much vocabulary should be taught or learned daily, weekly, or yearly, as it is a concept that tends to show discrepancy due to two factors: first, there might be differences in learners’ vocabulary acquisition skills; and second, the term is too broad to be situated within a context where it can be measured precisely. In light of this explanation, the researcher, for the convenience’s sake, decided to include only 80 words in the list. This way, participants would need to learn a maximum of 20 words per week –a number which is neither too large nor too insignificant, considering the time constraints and the burden of other academic tasks the participants had.

After the pre-test results were analyzed and the words known by the majority of participants (75% or more) were eliminated, the remaining vocabulary items were used to create the study materials. First, the group of words that were not answered correctly by at least 75% of participants was divided into four sets, to be handed to the participants each consecutive week. The participants were not provided with mere translations of the technical vocabulary (see Appendix 7); definitions of each term in their native tongue were also prepared using ChatGPT to help them internalize the words more effectively in order to prevent misapprehension.

In the preparation of the study materials, the researcher followed the explanation made by Anderson and Nagy (1993), who stated that vocabulary should be taught in an enjoyable setting, which in turn invokes learners' curiosity and makes the whole process more productive. In this case, as the repetitive activities could make the whole learning experience feel monotonous from the participants' perspective, the activities were designed to provide the participants with an experience that was educational, fun, and creative. Thus, with the help of ChatGPT, three different types of exercises were created. Each week, students were taught under the guidance of the researcher by engaging with these exercises. Per week, study materials that contained 20 new words (10 words for the final week) were distributed to the participants.

The first exercise was a vocabulary-to-image matching activity (see Appendix 8). In this task, participants were asked to match nouns with the corresponding images below them. This activity was used only for specific nouns that had visual representations. Given that they would prove to be quite challenging to be depicted through images, verbs and adjectives were not included in this part. Instead, these types of words were listed alongside their Turkish definitions, which were given in an incorrect order across from them, and the participants were asked to match each term with its L1 equivalent (see Appendix 9).

The second type of activities consisted of context-based fill in the blanks exercises that allowed the participants to get a chance at seeing how the target words were used in real life, authentic contexts. These activities were prepared with the intention of serving the participants' lexical needs. As shown in Appendix 10, the participants were asked to read each sentence and place the word that completed it. These activities would not only help them learn the target words, but also teach them how to use these words accurately in context.

The final type of activities consisted of translation-based L1-to-L2 active recall activities. In these exercises, the participants were asked to write the English definitions of the words provided to them in their native language. A sample of this activity can be seen in Appendix 11.

3.5. Setting and Participants

The research in question was conducted in the Maritime Transportation and Management Engineering Department at Karadeniz Technical University. Initially, there were 76 participants who were in their freshman year, with ages ranging from 18 to 20. The participants were selected using the convenience sampling method. The sampling was based on the criteria that the participants were studying at the department in question and had received a minimum of one semester of education in the said field. Although the starting number was 75, it was reduced to 64 due to the fact that 11 participants who took the pre-test did not take the post-test. The gender distribution of the participants of the study, as can also be seen in Table 5**,** was not fully homogeneous, as the number of male participants (n = 46) outweighed the number of female participants (n = 18)**.**

Table 5: Demographic Information of the Participants

Categories		**N**	**%**
Gender	Male	46	72
	Female	18	28
	Total	64	
Age	18-20		
Department	Maritime Transportation and Management Engineering		

3.6. The Qualitative Data

In order to gather the qualitative data for the study, a five-question questionnaire was prepared using Google Forms (Appendix 12). The link was then shared with the participants, and out of 64 participants, 36 took part in the questionnaire. The responses of the participants, then, were analyzed through thematic coding to identify recurring patterns and insights.

3.7. Data Analysis

To do the statistical analysis, after checking the pre-test and post-test papers, the results were saved in two separate Excel files with .csv (Comma-Separated Values) extensions. When a file is saved in .csv format, all the values inside the file are converted into plain text and automatically separated by commas, which in turn makes it easier for the analysis software to read the values. The layout of the Excel sheet can be seen in Appendix 13, with each row containing questions and each column representing the participant IDs.

After preparing the Excel files, each question was marked with zeros and ones depending on the nature of the answer. If the participant's answer was correct, the corresponding cell was marked with a "1", and if the answer given by the participant was incorrect, the cell was marked with a "0". For the purposes of making the analysis process smoother and less prone to errors, the researcher marked unanswered questions with "0" as well. The reason for this was that if the cells that correspond to unanswered questions were left empty, the software would see them as null values and throw errors or fail to acknowledge the empty cells entirely, which would cause a mismatch between the pre-test and post-test results. As a final step, the files were uploaded to SPSS software for statistical analysis.

CHAPTER FOUR

4. RESULTS AND DISCUSSION

4.1. Introduction

The purpose of the present mixed-methods study is to measure the degree to which the specifically designed study materials affect the acquisition of vocabulary on learners' part. By conducting a pre-test before the experimentation and a post-test after teaching the participants all vocabulary through the study materials, the researcher aimed to observe the curve the participants' learning followed. In the current section, each research question is answered. First, the accretion process of the Maritime Transportation and Management Engineering technical word list is explained. Second, the results of the pre-test and post-test are reported. Initially, pre-test and post-test were analyzed individually, and later, the results are compared.

4.2. Maritime Transportation and Management Engineering Technical Word List

The first research question was to find the most frequently used technical vocabulary in Maritime Transportation and Management Engineering research articles. Thus, a corpus (MAR-ENGCORP) containing research articles in the aforementioned field was compiled. The research corpus included 52 articles collected from Q1-ranked journals with SSCI and SCI indexing, which amounted to a total of 410,000 running words.

To create the technical word list, a frequency analysis would not suffice on its own. As a technical list is expected to include vocabulary that is specific to the field, the researcher had to ensure that the vocabulary making it to the final list lived up to the scope of this definition. For that reason, the frequency sorted words were compared to the two-word lists that hold high influence in the field of ELT, which are the GSL and the AWL.

The process of deciding the inclusion of certain vocabulary and the elimination of the rest was done through checking the first 450 vocabulary items sorted by Sketch Engine on the in-page filtered search bar built into the EAP Foundation website (Smith, n.d.). The built-in search bar could search vocabulary through both the GSL and the AWL, and return an answer that indicated the absence of the vocabulary in the word lists. On this note, the vocabulary that was found in neither list, which had a sum of 86 words, was gathered into a file to be sent to two AI chatbots, ChatGPT and Microsoft

Copilot. The words chosen by both chatbots as non-technical were removed from the list. The remaining vocabulary was deemed acceptable for the final list, which can be seen in Table 6.

Table 6: Maritime Transportation and Management Engineering Technical Word-List

Marine Sensor Magnetic Fluid Ballast DWT (Deadweight Tonnage) Trajectory Turbine Simulation Logistics Reactor Acoustic Observation Fuel Platform Measurement Connector Buoy Optical Rotor Array Subsea Collision Propulsion Cable Maintenance Configuration Stem	Navigation Pipeline Gear Calibration Regression Deepsea Mooring Cr (control room) Density Seafarer Salinity Storage Propeller Radar Seabed Tank Mapping Oceanography Manufacturer Turbulence Naval Velocity Torque Ferry Module Deploy REM (Remote Environmental Monitoring)	Grid Analyze Switchgear ROV (Remotely Operated Vehicle) Diesel Autonomous Fatigue Transformer Install Accelerate Lidar (Light Detection and Ranging) Vertical Forecasting Offshore Aquaculture Novel Underwater MRE (Marine Renewable Energy Spatial Coastal Industrial Operational Voltage Tidal Schematic

4.2.1. Lexical Characteristics of the Pre-Test Word List

Even though the study's primary focus was on individual technical vocabulary items rather than multi-word phrases, in order to gain a better understanding of how these terms generally appear in authentic documents, an analysis of their contextual usage was considered necessary To do that, the first five most frequently occurring items from the pre-test list (marine, datum, sensor, offshore, and DWT) were analysed in terms of their co-text and recurrent patterns to gain a better understanding of the contextual behaviour of the technical vocabulary that were chosen to be used in the study. In order to extract these concordance lines from the MAR-ENGCORP, the KWIC function of Sketch Engine was used. The main goal was to ensure that these items occurred in predictable and pedagogically beneficial patterns, in addition to being semantically relevant to the field. Because it guarantees that the phrases are used in situations that are common for ESP learners in fields relevant to the maritime industry, this study supports the inclusion of the contextual patterns of the five vocabulary items that appeared most frequently in the MAR-ENGCORP.

Table 7: Contextual Patterns of the Technical Word List

Left Context	Word	Right Context
This is especially true for	marine	Biotechnology that directly addresses global societal challenges
These entail transdisciplinary collaborations that maximize the sharing of a key	datum	And knowledge, and, consequently, results and potential technology transfer
Each	sensor	has dedicated procedures for maintenance, usually described by the manufacturer manuals or in relevant Best Practices reports available in the community
Coatings combined with cathodic protection are the most common tools used for the protection of materials in	offshore	environments
300 000	DWT	tanker for this size and type of ship the maximum power capacity installed, excluding the emergency generator capability, was taken to be 29.7 MW

4.2.2. Development of Study Materials

Following the formation of the technical word list, via the application of the pre-test, the words known by at least 75% of the participants were detected. These words were later included neither in the post-test nor in the preparation of the study materials. The words eliminated from the pre-test can be seen in Table 8 below.

Table 8: Eliminated Words From the Pre-Test

Word	Word
Sensor	Fuel
Magnetic	Cable
Turbine	Radar
Simulation	Analyze
Reactor	Voltage

The eliminated vocabulary shown in Table 8, though different in nature, had some common features which rendered them unfit for the study materials. First, when the vocabulary in the above list is checked, the words “turbine”, “reactor”, and “radar” can be found to be nearly identical to their translations used in the participants’ native language. Similarly, words like “sensor”, “magnetic”, “simulation”, “cable” “analyze”, and “voltage”, though showing some differences from their Turkish equivalents, are again easy to guess for the participants, as the difference is minimal and the meaning of the words is easy to guess. At first glance, "fuel" and "cable" might be thought to be quite different from their translations in the target language of the participants; however, considering the wide use of English, it is safe to presume that a majority of the participants have, at least once, seen or heard these terms in their daily life. Subsequent to the elimination process, the remaining 70 words were used in the preparation of the study materials and the post-test.

4.3. Pre-Test and Post-Test Analysis

4.3.1. Pre-Test Results

To analyze the pre-test data, a dependent samples t-test was used. The statistical analysis of the raw data was conducted using SPSS. Calculations were made based on the 1s and 0s, with 1s indicating the correct answers and 0s indicating either incorrect responses or questions that were left blank. The statistical analysis of the pre-test is shown in Table 9.

Table 9: Pre-Test Statistics

	Mean Score (M)	**N**	**Standard Deviation (SD)**	**Std. Error Mean (SEM)**
Pre-Test	18.6094	64	10.50717	1.31310

Upon the analysis of the pre-test data, it was found that the mean score ($\mu = \Sigma X_i / N$) of the test was M = 18.60. This indicates that approximately 26.58% of the questions were answered correctly. The standard deviation ($\mathrm{sqrt}[\ \Sigma(X_i - \mu)^2 / (N - 1)\ ]$) of the pre-test was calculated as SD = 10.50717. In Barde and Barde's (2012) words, SD gives information about how far the observed values are spread from the mean. A small SD typically means the dispersion was small, that is, the observed values performed similarly, and a large SD, understandably, points toward wide separation of the values (Barde & Barde, 2012). In this study, the SD was found to be SD = 10.50717, which indicates that the participants performed differently. Due to the nature of this study, a wider spread among the pre-test results of the participants suggests that there was variety among the participants' scores, which is a benefit, as it means the chances of the participants copying off of each other's papers were low.

The standard error of the mean (SEM) score of the pretest (SD / sqrt(N)) was found to be SEM = 1.31310. The SEM refers to the fluctuations in the mean score if the study were to be repeated (Lee et al., 2015). While the SEM of the pre-test does not mean much on its own, it is still necessary for the computation of the 95% confidence interval (CI) in the dependent samples t-test (Andrade, 2020).

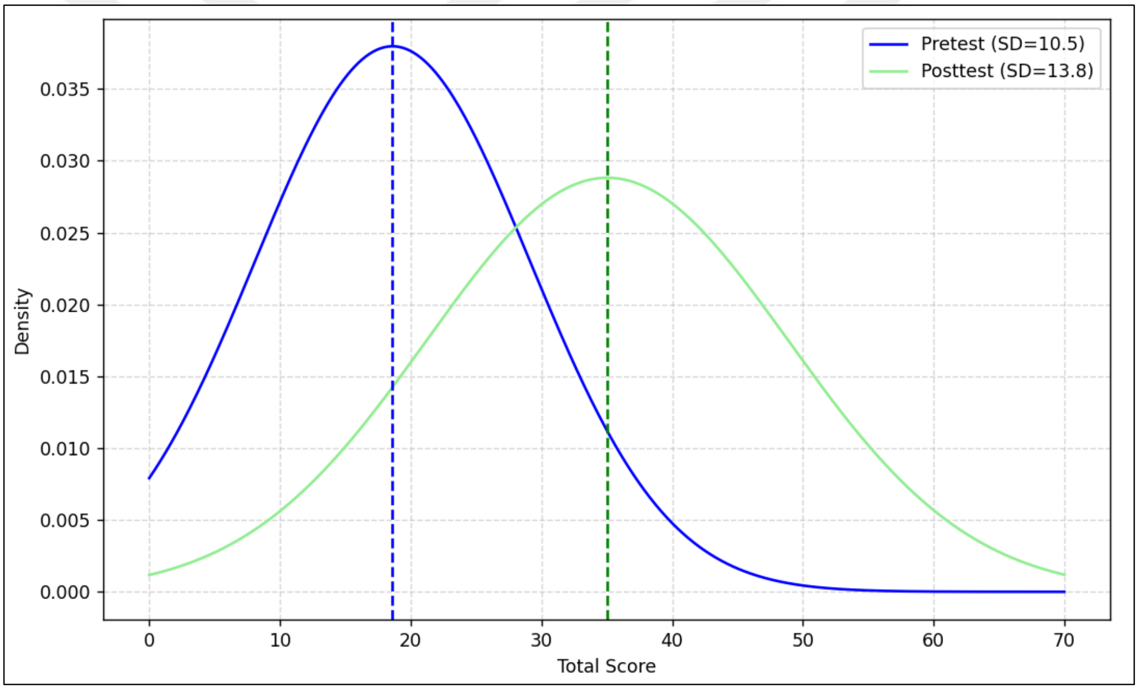
4.3.2. Performance Analysis Between Pre-Test and Post-Test

Table 10: Post-Test Statistics

	Mean Score (M)	N	Standard Deviation (SD)	Std. Error Mean (SEM)
Post-Test	35.0469	64	13.84429	1.73054

Before delving into the dependent samples t-test, it is necessary to check the post-test statistics. As presented in Table 10, the mean score of the post-test results (M = 35.0469) indicates an improvement, with approximately 50.06% of the questions answered correctly.

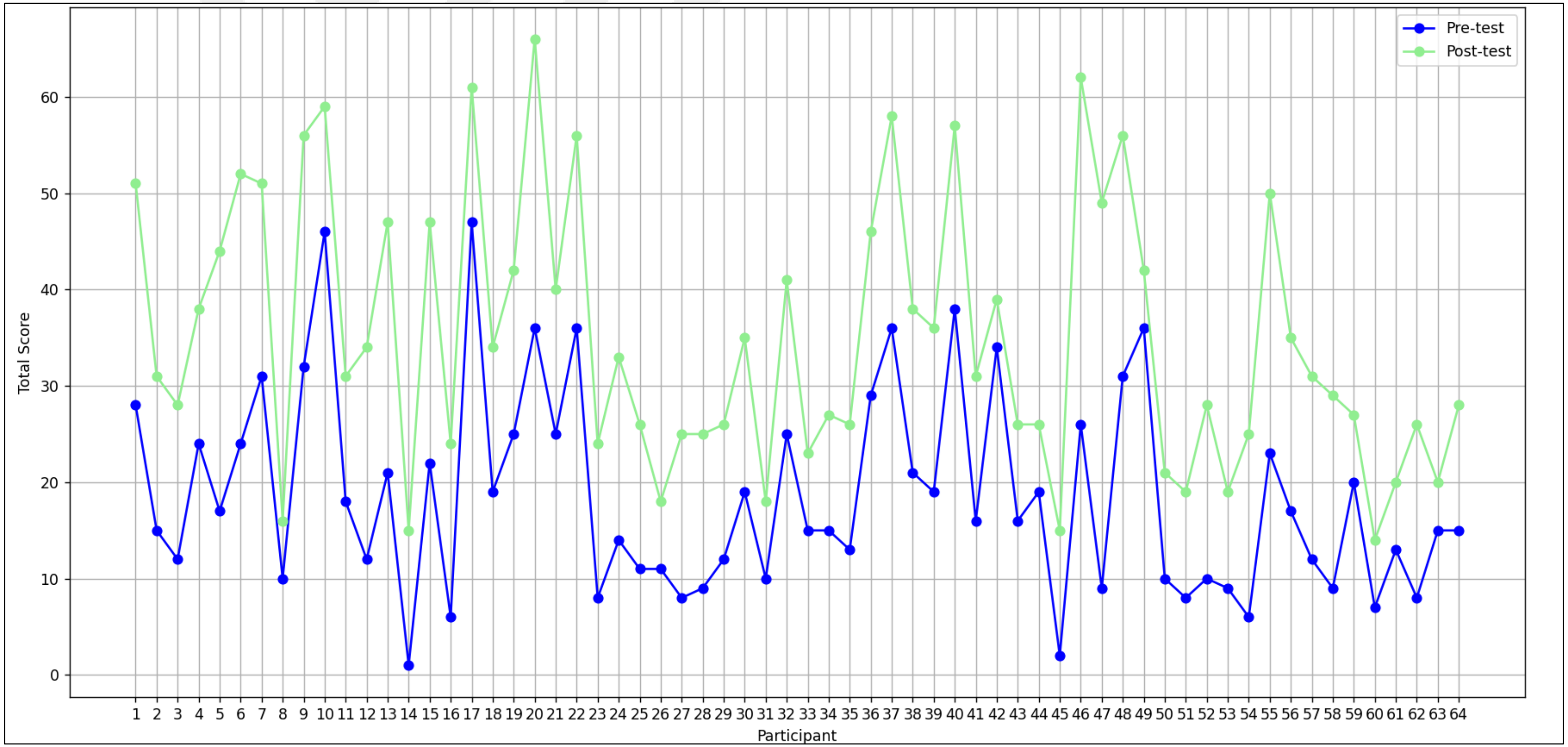
Figure 5: Gaussian distribution of Pre-test and Post-Test SD



Note: The x-axis indicates the total score of the tests (70 questions), and the y axis indicates the frequency distribution of specific scores.

As for the SD scores of the pre-test (SD = 10.5) and the post-test (SD = 13.5), a change is observed. When Figure 5 is analyzed, it can be seen that the shape of the bell curve of the post-test SD shows some interesting discrepancies when compared with the pre-test SD. For instance, the bell curve of the post-test is wider and shorter. This indicates two things. First, the width of the shape indicates the uniformity of the test results: the narrower the shape, the more similar the results are. What this means for the post-test SD is that the effect of the intervention was not equal for each participant; that is, some of them showed great improvement while others did not. Additionally, the height of the curve indicates the probability density of the scores given on the x-axis. In that regard, it is clear that even though the SD score of the post-test was less uniform compared to the pre-test, the number correct answers given by each participant increased, and the percentage of correct answers is clustered more towards the top score.

Figure 6: Scores of Each Participant in Pre-Test and Post-Test



The total score of each participant is shown in Figure 6. When the total number of correct answers of the participants in the pre-test is compared to the post-test results, an upward trend is observed. In the following sections, the participants will be divided and grouped into four categories based on the progress they made in the post-test.

4.3.2.1. Participants with Low Increase (0 – 10) in Post-Test Scores

In the current study, only 13 participants (18.57%) were found to have shown low performance. In this segment, the participants who had an increase falling between 1 and 10 correct answers will be discussed in detail.

Table 11: Participants with 0 – 14.28% Increase

Participant ID	Pre-Test Correct Answers Percentage (%)	Post-Test Correct Answers Percentage (%)	Total Increase Percentage (%)
8	14.28	22.85	8.57
26	15.71	25.71	10
31	14.28	25.71	11.42
33	21.42	32.85	11.42
42	48.57	55.71	7.14
44	27.14	37.14	10
49	51.42	60	8.57
59	28.57	38.57	10
60	10	20	10
61	18.57	28.57	10
63	21.42	28.57	7.14
43	22.85	37.14	14.28
53	12.85	27.14	14.28

The information of each participant in this range is presented in Table 11 above. Drawing from that information, the participants who showed the least improvement between pre-test and post-test are participants *42* and *63*. These participants had an increase of 5 (7.14%) correct answers in their post-test, which is followed by participants *8* and *49* with an increase of 6 (8.57%) correct answers. Participants *26, 44, 59, 60,* and *61* showed a 7-point (10%) improvement, and the remaining two, *31* and *33,* had 8 (11.42%) more correct answers in their post-test. Finally, participants *43* and *53* reached the ceiling score of this category by answering 10 (14.28%) more questions correctly.

4.3.2.2. Participants with Moderate Increase in Post-Test Scores (11 – 20)

Similar to the previous section, participants who were observed to have increased the number of their correct responses by 11 to 20 —a ten-point range— are placed in the moderate increase group. The participants who fall under this category make up 57% (N = 37) of the total sample population (N = 64) (see Table 12).

Table 12: Participants with 15.71 – 28.50% Increase

Participant ID	Pre-Test Correct Answers Percentage (%)	Post-Test Correct Answers Percentage (%)	Total Increase Percentage (%)
2	21.42	44.28	22.85
3	17.14	40	22.85
4	34.28	54.28	20
7	44.28	72.85	28.57
10	65.71	84.28	18.57
11	25.71	44.28	18.57
14	1.42	21.42	20
16	8.57	34.28	25.71
17	67.14	87.14	20
18	27.14	48.57	21.42
19	35.71	60	24.28
21	35.71	57.14	21.42
22	51.42	80	28.57
23	11.42	34.28	22.85
24	20	47.14	27.14
25	15.71	37.14	21.42
27	11.42	35.71	24.28
28	12.85	35.71	22.85
29	17.14	37.14	20
30	27.14	50	22.85
32	35.71	58.57	22.85
34	21.42	38.57	17.14
35	18.57	37.14	18.57
36	41.42	65.71	24.28
38	30	54.28	24.28
39	27.14	51.42	24.28
40	54.28	81.42	27.14
41	22.85	44.28	21.42
45	2.85	21.42	18.57
50	14.28	30	15.71
51	11.42	27.14	15.71
52	14.28	40	25.71
54	8.57	35.71	27.14
56	24.28	50	25.71
57	17.14	44.28	27.14
58	12.85	41.42	28.57
62	11.42	37.14	25.71
64	21.42	40	18.57

Out of 39 participants, the lowest scoring individuals in this group are participants *50* and *51*, with an 11-point (15.71%) increase in their post-test results, who are closely followed by participant *34*, whose score increased by 12 points (17.14%), and participants *10*, *11*, *35*, *45*, and *64* with a 13-point (18.57) improvement. The rest of the participants follow a pattern in which accuracy increases by one point. Participants *4*, *14*, *17*, and *29* had a 14-point (20%) increase in correct answers, followed by participants *18*, *21*, *25*, and *41* with 15 (21.42%); *2*, *3*, *23*, *28*, *30*, and *32* with 16 (22.85%); *19*, *27*, *36*, *38*, and *39* with 17 (24.28%); *16*, *52*, *56*, and *62* with 18 (25.71%); and *24*, *40*, *54*, and *57* with 19 (27.14%). The highest increase observed in this group was shown by participants *7*, *22*, and *58* with 20 correct answers (28.57%) in the post test.

4.3.2.3. Participants with High Increase in Post-Test Scores (21 – 30)

Unlike the preceding group, the participants who comprise the 15.71% (11) of the total population (N = 64) in this category showed high-improvement, with an increase of 21 to 30 correct answers in the post-test (see Table 13).

Table 13: Participants with 30 – 42.85 % Increase

Participant ID	Pre-Test Correct Answers Percentage (%)	Post-Test Correct Answers Percentage (%)	Total Increase Percentage (%)
1	40	72.85	32.85
5	24.28	62.85	38.57
6	34.28	74.28	40
9	45.71	80	34.28
12	17.14	48.57	31.42
13	30	67.14	37.14
15	31.42	67.14	35.71
20	51.42	94.28	42.85
37	51.42	82.85	31.42
48	44.28	80	35.71
55	32.85	71.42	38.57

The third category starts with participants *12* and *37*, whose scores went up by 22 points (31.42%) in the post-test. The majority of participants in this group followed a similar growth pattern, each improving incrementally by one point. For example, following the pre-test, in their post-test participant *1* answered 23 questions correctly (32.85%); participant *9*, 24 (34.28%); participants *15* and *48*, 25 (35.71%); participant *13*, 26 (37.14%); participants *5* and *55*, 27 (38.57%); and finally participant *6* answered 28 questions correctly (40%). The participant who had the highest post-test accuracy in this group was participant *20*, who answered 30 points correctly in the post-test (42.85%).

4.3.2.4. Participants with the Highest Increase in Post-Test Scores (31 – 40)

This group includes the participants that showed the highest performance in the aftermath of the intervention. Only 2.85% (N = 2) of the total population were observed to achieve a significant increase in correct answers on the post-test, within a range of 31 to 40.

Table 14: Participants with 44.28 – 57.14 % Increase

Participant ID	Pre-Test Correct Answers Percentage (%)	Post-Test Correct Answers Percentage (%)	Total Increase Percentage (%)
46	37.14	88.57	51.42
47	12.85	70	57.14

As shown in Table 14, the only participants who are considered to have shown a sharp increase in accurate answers in their post-test results are *46* and *47*. Participant *46* increased their correct answers to *36* (51.42%), and *47* exceeded it by scoring 40 (57.14%) correct answers.

4.3.3. Dependent Samples T-Test

Regarding the results of the dependent-samples t-test, as shown in Table 15, it was revealed that the post-test showed a statistically significant difference from the pre-test ($t = 18.236$, $p < 0.001$). The p-value being smaller than 0.05 rejects the null hypothesis, which suggests that there is no difference between the means of the compared values (Frick, 1995). Additionally, in Sawilowsky's (2009) classification, a Cohen's d value larger than 2.0 indicates a huge effect size.

Table 15: Dependent Samples Test Results

	Mean	STD	95% Confidence Interval of the Difference (CI)	T Value	DF	P Value	Cohen's D
Pre-Test - Post-Test	-16.43750	-7.21083	Lower Upper -14.63629 - 8.23871	-18.236	63	<.001	2.280

4.3.4. Question Level Analysis

In this section, beyond analyzing total test scores, a question-level analysis is conducted to assess the distribution and change in correctness for each individual question across the pre-test and post-test. This approach provides insights into which words were generally known by participants before instruction and which ones showed greater learning gains after the intervention. For each item, the number of correct responses was counted in SPSS, and comparisons were made between the two testing points, as also shown in Figure 7 below. This analysis, which offered a more detailed view of participants' vocabulary development, helped reveal patterns in item difficulty and learning effectiveness at a granular level.

Figure 7: Heat-Map of the Patterns in Question Difficulty

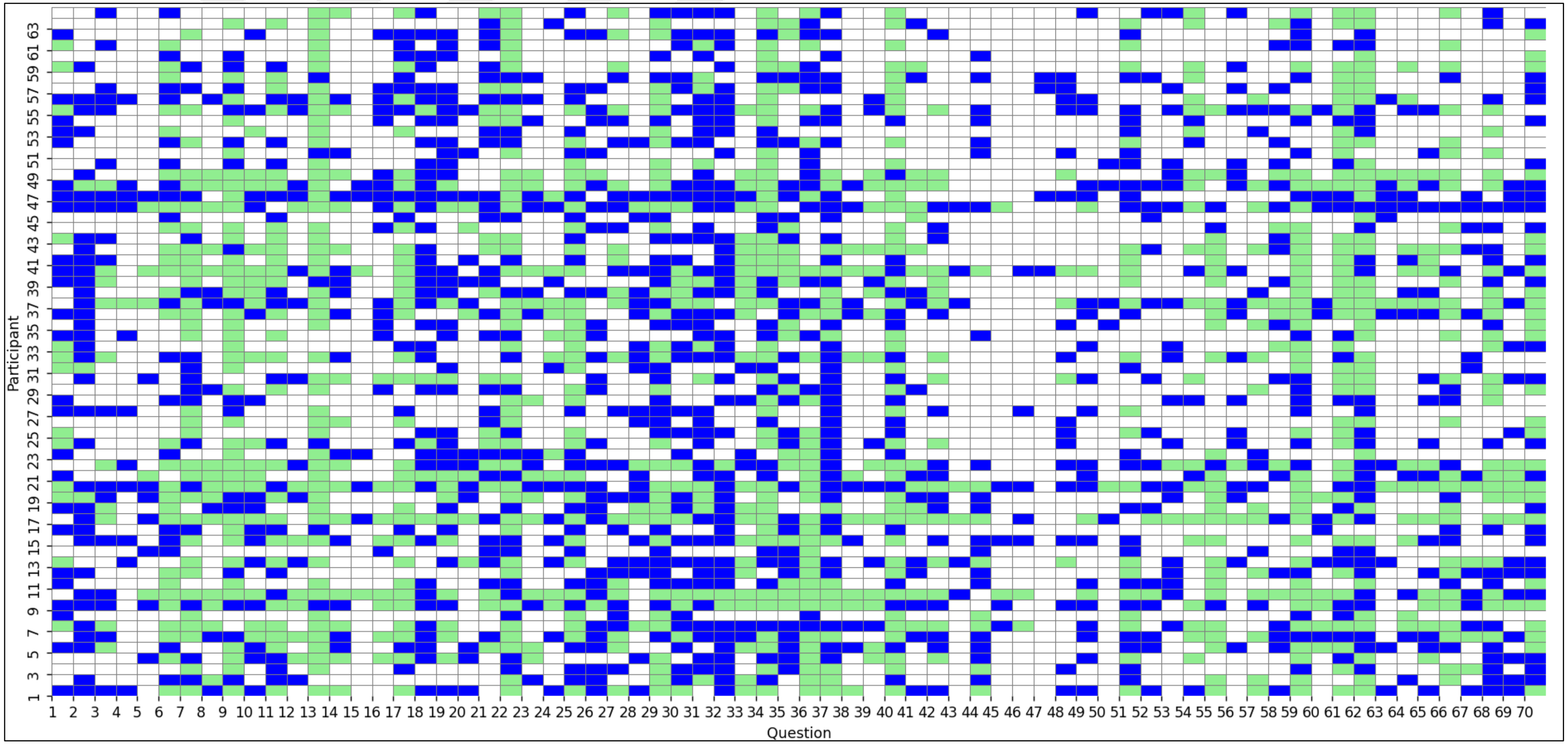


Figure 7 above presents the patterns in question difficulty, illustrating the participants' performance for each question before and after the intervention. The green-colored cells indicate the questions that were not answered correctly in the pre-test but were improved in the post-test. The blue colored cells, on the other hand, represent the questions that were answered correctly in both tests. Finally, the empty cells indicate the questions that were answered incorrectly or left blank in both tests. In the following sections, the top 20 questions that showed the greatest improvement and the top 20 questions that showed the least improvement will be analyzed.

Table 16: The Top 20 Questions That Showed the Most Improvement After the Intervention

Question ID	Pre-test Correct Answer Count	Post-Test Correct Answer Count	Pre-Test Post-Test Improvement
32	3	46	43
18	5	42	37
31	13	49	36
37	19	54	35
2	3	38	35
26	2	31	29
30	12	40	28
19	14	41	27
62	36	61	25
1	14	38	24
70	27	50	23
25	31	53	22
29	34	56	22
21	19	41	22
22	39	60	21
34	39	60	21
49	4	24	20
51	24	43	19
53	2	21	19
28	6	25	19

The list of the top 20 questions that showed the most improvement after the pre-test can be seen in Table 16. When the list is examined, it can be seen that the improvement in correct answers post intervention ranged from 19 to 43. With that in mind, if the questions were to be grouped further, it could be said that 75% (N = 15) of the questions that showed the most improvement, which are *32* ("Salinity"); *18* ("Propulsion"); *31* ("Seafarer"); *2* ("Fluid"); *26* ("Regression"); *30* ("Density"); *19* ("Maintenance"); *25* ("Calibration"); *29* ("Cr"); *21* ("Stem"); *22* ("Navigation"); *34* ("Propeller"); *49* ("Switchgear"); *51* ("Diesel") and *53* ("Fatigue") were nouns. Following that, 15% (N = 3) of the questions in the list, which are *1* ("Marine"); *70* ("Schematic") and *62* ("Novel") were adjectives. The remaining 10% (N = 2) which were *37* ("Mapping") and *28* ("Mooring"), were verbs. Based on this data, it can be said that the majority of the questions that showed the greatest improvement consisted of nouns.

Table 17: The Top 20 Questions That Showed the Least Improvement Post Intervention

Question ID	Pre-test Correct Answer Count	Post-Test Correct Answer Count	Pre-Test Post-Test Improvement
27	23	33	10
63	4	13	9
5	5	13	8
24	12	20	8
60	7	15	8
57	16	23	7
38	9	16	7
39	14	21	7
8	15	21	6
33	26	31	5
13	51	56	5
15	2	7	5
46	2	7	5
64	18	23	5
43	4	7	3
50	3	6	3
54	24	27	3
66	36	39	3
47	2	4	2
45	4	6	2

The questions that showed the least improvement are listed in Table 17. Upon further analysis, it is seen that the majority of the items in the list —*27* (“Deepsea”), *63* (“Underwater”), *24* (“Vertical”) *60* (“Offshore”), *38* (“Spatial”), *33* (“Tidal”), *13* (“Optical”), *54* (“Naval”), *66* (“Coastal”), and *45* (“Velocity”)— were adjectives. While adjectives accounted for 50% (N = 10) of the total list, nouns followed closely with 45% (N = 9). The nouns in the list are as follows: *5* (“Trajectory”), *57* (“Lidar”), *39* (“Manufacturer”), *8* (“Observation”), *15* (“Array”), *64* (“MRE”), *43* (“Torque”), *50* (“ROY”), and *47* (“REM”). Finally, with a frequency of 5% (N = 1), *45* (“Deploy”), a verb, concludes the list.

4.4. Qualitative Data Analysis

Table 18: Thematic Coding of the Qualitative Data

Theme	Code	N	%	Participant Response
Engagement and Usefulness	Found activity fun / useful / engaging	36	100%	“Yes, it was fun and pleasant.”, “Yes, it was helpful and engaging.”, “Yes it was enjoyable and informative.”
Vocabulary Improvement	Reported vocabulary improvement	35	97.2%	“I learned the words better”, “After the activities, I was able to understand the words better”, “Yes, I think so. It has improved quite a lot.”
Ease of Learning	Daily, short, or previously seen words	6	16.6%	“I found short and everyday words easy to recognize.”, “It was a lot easier for me to learn the words I’ve seen before.”
	All of them	6	16.6%	“It was easy to learn all of them”, “All of them”, “All words were easy to understand and clear”
	Discipline-related or L1-related words	6	16.6%	“Marine English”, “Terms related to my profession.”
Total		18	50%	
Learning Challenges	Long, strange, or unfamiliar words	6	16.6%	“Long words.”, “Some strange words.”, “Words I have not encountered in my life.”
	General difficulty	11	30.5%	“Not except some words.”, “Some words.”
Total		17	47.2%	

Apart from the quantitative data collected through the pre-test and post-test, participant reflections on the technical vocabulary and study materials were also gathered via a questionnaire and analyzed qualitatively. The total number of participants who took the questionnaire was 36. The responses given to the open-ended questions were analyzed, coded, and finally grouped under five themes, which are presented in Table 18.

According to the thematic analysis, most participants answered the question asking about the usefulness and engagement of the study materials with a simple “yes” or “I did” while some others elaborated on it with comments such as “Yes, it was helpful and engaging.” (Response 10), “Yes, it was fun and pleasant.” (Response 7), or “yes it was enjoyable and informative.” (Response 11). Regarding the second question, which explored the effect of the study materials in helping the participants learn the technical vocabulary better, the majority of responses were positive, and pointed to increased competence and confidence as the participants commonly expressed with comments such as “yes I believe it's getting better the more I practice.” (Participant 22), “I was able to understand the words better after the activities.” (Participant 8), “my understanding of the words improved.” (Participant 6), and “The words were easier in the second test.” (Response 7), all suggesting that the exercises helped them improve their technical knowledge, and contributed to their success in the post-test.

For the third question, which investigated the participants about vocabulary items that were difficult to learn, 51% of the population reported that there was no particular vocabulary with which they had trouble learning. Among the remaining responses, several noted difficulties with unfamiliar or longer technical terms, including “Words I haven’t encountered in my daily life.” (Response 4), “long words” (Response 6), “Some strange words” (Response 7), “A few of the long ones” (Response 11), and “Schematic” (Response 9).

Regarding the final question on the vocabulary that was easiest to learn, responses were mostly centered around words that were similar, or identical in spelling to the participants’ L1, such as “I remember only sensor and turbine” (Response 6), “Sensor and radar” (Response 9), words that they have encountered or heard before; “Words that are used in daily life.” (Response 2), “Short words that I come across in everyday situations.” (Response 7), “The words we had seen before in our classes.” (Response 8), “It was easier to learn the words I was already familiar with..” (Response 30).

All in all, the feedback gathered through the questionnaire supports the practicality and efficacy of the study materials, with the majority of the participants providing positive feedback.

4.5. Discussion

The focus of this mixed-methods research paper was creating a technical word-list for the Department of Maritime Transportation and Management Engineering, developing study materials based on the selected words with the purpose of teaching them to the participants of the study, and subsequently measuring the impact of these study materials on the participants. Following this process, the participants were, then, asked to fill out a questionnaire regarding their perception of the word-list and the study materials.

This research posed the following research questions.

R.Q.1. What is the commonly used vocabulary in Maritime Transportation and Management Engineering research articles?

After compiling the MAR-ENGCORP from the research articles relevant to the field for which the word list is prepared, the corpus was transferred to Sketch Engine for frequency analysis. Following this process, the first 450 words —minus the function words such as “the” and “and”— were sorted by frequency and cross-checked against both the AWL (Coxhead, 2000) and the GSL

(West, 1953) to sort out the vocabulary items that already occurred on these lists. Of the 450 words, 364 of them were found to be present in either the AWL or the GSL. The remaining vocabulary (N = 86), for further refining purposes, was uploaded on two chatbots, ChatGPT and Microsoft CoPilot, and a prompt was entered requesting the chatbots to identify the words that were not related to the field. The words both chatbots deemed as unsuitable for a technical word list were removed, and as a final step, following the refined list was reviewed by both a linguist and a field expert, resulting in the creation of the Maritime Transportation and Management Engineering technical word list.

The final 86 technical vocabulary items that were produced through this process represent highly domain-specific terminology exclusive to the learners in the field. The relevancy of the contents of the list was ensured via a multi-step refinement process (corpus analysis, crosschecking against the AWL and GSL, AI-assisted filtering, and expert assessment). This four-pronged approach improved accuracy of the list by producing a concentrated list of vocabulary items for the use of the students of the field in question. However, due to the nature of AI language models — e.g. the training data and constraints—, relying on AI-based filtering may introduce subjectivity to a degree. In the current study, for example, while ChatGPT found only nine words to be eliminated, Microsoft CoPilot selected 13 words that it deemed non-technical.

R.Q.2. To what extent do customized-study materials influence students' vocabulary learning outcomes?

After analyzing the statistical difference between pre-test and post-test results, it was discovered that the intervention had a positive effect on participants' performance ($p < .001$). This finding was also supporting previous research by demonstrating a meaningful increase in vocabulary acquisition post targeted instruction (Anwer, 2019). Upon analyzing the performance of each participant following the intervention, it was discovered that each participant experienced an increase in their test scores. In order to investigate the extent of individual improvement, participants were grouped into four categories based on the increase in their scores. 20% of the population were in the first category, containing the participants with a relatively low increase (1-10 correct answers) in their post-test. The second category, under which the majority of the participants fell, had participants with a moderate increase (11-20 correct answers). The third category included participants (16%) who performed a high increase (21-30 correct answers) in the wake of the intervention, and the final category included participants (2.85%) who exhibited the highest increase in their post-test results (31-40 correct answers). The fact that only one-fifth of the total population was included in the low increase group, and that the majority of participants were observed to have scored above 11 correct answers in the post-test, combined with the extremely small p value of <.001, indicates that the study materials had a statistically significant impact on the participants' vocabulary learning outcomes.

The triangulated structure of the study materials, which incorporated three types of exercises: vocabulary-to-image matching, context-based fill-in-the-blank activities, and translation-based tasks, can be the reason why they were effective. There are two reasons why this approach produced strong such results: (a) the study materials included varied types of activities, which matches August et al.'s (2021) findings, that is, the use of a multifaceted approach in vocabulary instruction benefits the learners in terms of vocabulary retention, and (b) the majority of the activities were context based, featuring authentic and field related sentences generated by ChatGPT. As also emphasized by Tosuncuoğlu (2015) and Nation (2005) these types of sentence-based activities are more effective in teaching vocabulary than simple memorization activities where learners try to memorize decontextualized vocabulary.

R.Q.3. Which vocabulary items showed the greatest and least improvement from pre-test to post-test, and what might explain these differences in learnability?

When the top 20 questions that showed the greatest increase in the post-test were analysed, it was found that 75% of the items consisted of nouns, while verbs accounted for 15% of the total list, followed by adjectives that constituted the 10% portion of the technical word-list. When the same approach was applied to the top 20 questions that showed the least improvement in the post-test, the results indicated that adjectives were the most prominent type of vocabulary with 50% occurrence rate. After the adjectives, nouns took the second place with 45% occurrence rate which were followed by verbs that accounted for the remaining 5%. However, before drawing conclusions, it is important to note that a third of the nouns in the 45% segment were not single words but compound terms such as "MRE", "ROY" and "REM", which can be challenging for some to learn due to their complex structure. To learn such terms, the learners not only have to memorize more than one word, but also try to remember the meaning of each term that makes up the acronym. This adds to the memorization workload, making the memorization process longer and thus, causing cognitive fatigue. This pattern also aligns with previous research, which suggests that the acquisition and use of compound nouns can pose greater challenges than single nouns (Schmitt & Zimmerman, 2002; Libben, 1998). With that in mind, it becomes evident that the word type that showed the greatest improvement was single nouns, whereas the one that showed the least noticeable improvement was the adjectives. This finding corroborates existing research in the literature. In Gasser and Smith's (1998) study, it was revealed that from a cognitive perspective, nouns—thanks to their concrete nature, making them easier to visualize and thus memorize— are easier to learn compared to adjectives, which tend to be more abstract. These findings imply that combining various teaching approaches, especially the ones based on real-world context, might significantly enhance students' learning of technical vocabulary in ESP settings.

Interestingly, while the vast majority of vocabulary items showed an increase from pre-test to post-test, one item —"install"—showed a small decrease, with 33 participants writing the correct answer across from the word in the pre-test but only 31 participants answering it correctly in the post-test. There could be several reasons to explain this. First, considering the influence of technology in their daily and academic lives, "install" is a word many students are already familiar with from general English, so they might not have paid much attention to it during the study, which might be the reason why some answered it incorrectly. Since it was not a completely new or field-specific word, it may have seemed less important compared to other unfamiliar terms Another reason could be that they might have confused it with “download”, which is often used synonymously in their L1. It is also possible that, with “install” being the 55th item on the post-test, some students were simply fatigued. On the whole, the overall trend of vocabulary gains remains robust and statistically significant.

R.Q.4. How do participants perceive the usefulness of the study materials and word list in learning technical vocabulary?

The qualitative data gathered from 36 participants after completing a five-question questionnaire strongly indicated that the participants were content with the technical word list, and the majority of them found the study materials fun and effective in helping them learn the vocabulary more easily. This supports the quantitative findings discussed in earlier sections, that is, the participants not only performed better after the intervention, but felt that the study materials were beneficial.

When asked about the most difficult vocabulary, some participants commented that longer words (compound nouns), some adjectives, or words they had never seen before were the most challenging for them to learn. These reflections align with the results of RQ3, where compound nouns and adjectives were discussed to be harder to learn compared to simple words (Schmitt & Zimmerman, 2002; Libben, 1998; Gasser and Smith; 1998). On the other hand, when asked about the easiest vocabulary items, participants predominantly referred to nouns they had heard before or the ones that resembled their L1 equivalents. Some participants reported that technical terms were easier for them to learn, such as “sensor” or “propeller” which might be due to the familiarity of the vocabulary. One possible explanation could be that, despite their specialized nature, these terms frequently appear in their field of study, which might lead to these words feeling more natural to students who are already familiar with the core concepts and basic vocabulary of the Maritime Transportation and Management Engineering department. Another explanation could be that since these vocabulary items were taught to the participants within field-specific contexts, it was easier for them to memorize and retain the meanings of certain words, a notion which supports Nation’s (2005) argument that learning vocabulary in meaningful context can improve learning and memorability. Everything considered, the participants’ feedback not only provided confirmation of the usefulness of the study materials, but also offered insights into how learners processed and remembered technical vocabulary.

To sum up, the results of this study point to the value of using corpus-informed, field-specific vocabulary teaching in Maritime English. The study materials not only helped learners improve their scores on the tests, but they were also seen by the majority of the participants as useful and appropriately challenging. These findings support what many ESP researchers have been saying: students benefit more from vocabulary that reflects the actual language used in their field. These findings add to the expending ESP research, highlighting the importance of real-world, context-relevant vocabulary training and imply that in order to maximise vocabulary learning, future materials should take learner familiarity and word type into account.

CONCLUSION AND RECOMMENDATIONS

This thesis, by determining the technical vocabulary specific to the Department of Maritime Transportation and Management Engineering and developing pedagogic resources to aid vocabulary acquisition, aimed to answer the requirement for field-specific vocabulary instruction in Maritime English. To the best of the researcher's knowledge, although there have been numerous studies conducted for the purpose of creating technical wordlists for various fields (e.g., Chen & Lei, 2019; Coxhead et al., 2016; Mukundan & Jin, 2012), too little attention has been paid to Maritime Transportation and Management Engineering department. In order to close this gap, this study used a multifaceted approach to create a customized technical word list for the use of the students of the field, along with specialized study materials prepared with the purpose of teaching the words to the participants of the study.

The technical word list created for this study, which is composed of 70 vocabulary items, was found to account for 2.95% of the total research corpus (N = 410,000). The number, though at first sight appearing to be small, is actually notably high considering the small size of the word list, especially when compared to word lists such as the AWL (Coxhead, 2000) which covered approximately 10% of the academic texts that composed the corpus of the study with 570-word families. The coverage of the technical word list suggests that the vocabulary selected from the MAR-ENGCORP are highly representative of the Maritime Transportation and Management Engineering field, which means the list represents a concentrated set of technical vocabulary that are used frequently in articles published within the scope of this field. This confirms the list's educational usefulness for students wanting to improve their field-specific lexical competence and validates the legitimacy of the word selection process.

Another important contribution of this study to the field is the set of study materials prepared specifically for students in the Department of Maritime Transportation and Management Engineering. Unlike generic vocabulary resources, in which vocabulary is taught in isolation, these materials, with the help of AI tools, were tailored to the actual lexical needs of learners in this specific field. Having access to vocabulary activities that reflect the real language used in the field can prepare the students for their future. The materials created are not only relevant to the field but also practical, especially because they present the target vocabulary in meaningful contexts. This makes them more engaging and useful for learners who want to improve their comprehension of the language and their overall confidence in dealing with situations where they would be needed to use English. Overall, this study shows that students do not just need to see technical words. They need well-prepared, clear materials that help them understand and remember those words in a meaningful context.

Finally, the Maritime Transportation and Management technical word list not only provides the practitioners and the professionals of the field with a specialized technical word list, and tailored study materials to teach those technical terms, but also greatly contributes to the teaching of discipline-specific vocabulary in the ESP research. Teachers working in ESP may find the technical word list and the study materials as beneficial tools for classroom use.

Implications

The analysis of the quantitative and qualitative data points to the pedagogical potential of incorporating customized materials into ESP instruction. Importantly, this research shows that even a small, carefully built corpus can be very useful if it is analyzed in the right way and combined with actual classroom practices. The improvements in the post-test scores support that focused vocabulary teaching works, and the fact that some types of words (e.g., short nouns) were easier to learn than others (e.g., adjectives or compound nouns) give useful clues for future material development.

The findings have implications for teachers and curriculum designers as well. In-service training for teachers on how to modify corpus-derived word lists for their curricula and assess vocabulary acquisition in ways other than frequency-based selection may be beneficial. Schools or departments might also consider offering support for training or tools that help teachers create materials with the help of AI.

Limitations of the Study

Despite the thesis contributing meaningfully to the field of Applied Linguistics, there are several limitations that need to be acknowledged. First, the sample population was not fully homogeneous in terms of gender, that is, the number of male participants constituted a larger percentage of the total population, greatly outnumbering the female participants. Second, because of time constraints, a delayed post-test could not be administered to participants, thus it was not possible for the researcher to evaluate how well vocabulary improvements were retained over time. Third, as the corpus was compiled from articles highly relevant to Maritime Transportation and Management Engineering department, the resulting word list would be limited to the confinements of this field and may not be generalizable to other engineering departments. Fourth, the study corpus was compiled solely from research articles related to the field. While through this approach the extraction of field-specific terminology was achieved, other types of texts, such as user manuals, textbooks, or dissertations related to the field in question, were excluded. Hence, the final list might not be fully representative of the complete vocabulary used within the field. Finally, as the study relied on AI filtering, there might be potential model bias due to the training data of the AI model.

Suggestions

The focus of the current thesis was on developing a technical word list specific to the Department of Maritime Transportation and Management Engineering, designing study materials based on the identified vocabulary, and evaluating the effectiveness of the study materials in teaching the target vocabulary to the participants through the administration of a pre-test and a post-test. For future research, the scope of this thesis could be expanded by increasing both the corpus size and participant number to enhance generalizability. Additionally, rather than concentrating solely on single-word units, phraseological structures and multi-word combinations relevant to the field under consideration could be investigated to provide a more comprehensive understanding of technical language use. Future research could also explore how the study materials could be turned into interactive websites or mobile apps, which would increase student engagement. Finally, with a more homogenous participant group, gender-based analyses could be conducted to explore potential differences in vocabulary acquisition between male and female participants.

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APPENDIXES

Appendix 1: Research Ethics Committee Approval

25.11.2024 14:11
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HİZMETE ÖZEL

KTÜ 1955

T.C.
KARADENİZ TEKNİK ÜNİVERSİTESİ REKTÖRLÜĞÜ
Hukuk Müşavirliği

Sayı : E-82554930-050.01.04-588545 25.11.2024
Konu : Atlas KÖROĞLU'nun Etik Kurul Kararı

Sn. Atlas KÖROĞLU

İlgi : 20.11.2024 tarihli ve E-26014373-050.01.04-586876 sayılı yazı.

KTÜ-Sosyal Bilimler Enstitüsü Batı Dilleri ve Edebiyatı Anabilim Dalı Uygulamalı Dil Bilimi Tezli Yüksek Lisans Programı öğrencisi Atlas KÖROĞLU'nun **"Curation and Development of Domain-Specific Terminology and Study Materials in Academic English Instruction: Maritime Transportation and Management Engineering"** adlı yüksek lisans tezi çalışması için gerekli Etik Kurul çalışması yapılmış ve başvurunuza onay verilmiştir.

Bilgilerinize ve gereğini rica ederim.

Prof. Dr. Ali TEMİZ
Rektör Yardımcısı

Bu belge güvenli elektronik imza ile imzalanmıştır.
Doğrulama Kod: 2391FD4E-F282-4338-9C8F-FF8F9F36F1A1 HİZMETE ÖZEL Doğrulama Adres: https://www.turkiye.gov.tr/karadeniz-teknik-universitesi-ebys

61080 – Trabzon / TÜRKİYE Tel: 04623772107 Faks: 04623774399 www.ktu.edu.tr Ayrıntılı Bilgi İçin İrtibat Belgin ŞEN hukukmusavirligi@ktu.edu.tr Sayfa 1 / 1

Appendix 1: (Continued)

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HİZMETE ÖZEL

T.C.
KARADENİZ TEKNİK ÜNİVERSİTESİ REKTÖRLÜĞÜ
Hukuk Müşavirliği

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Sayfa 1 / 1

Appendix 1: (Continued)

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HİZMETE ÖZEL

T.C.
KARADENİZ TEKNİK ÜNİVERSİTESİ REKTÖRLÜĞÜ
Sosyal ve Beşeri Bilimler Etik Kurulu

Sayı : E-26014373-050.01.04-586876 20.11.2024
Konu : Atlas KÖROĞLU'nun Etik Kurul Kararı

REKTÖRLÜK MAKAMINA
Hukuk Müşavirliği

İlgi : 01.11.2024 tarihli ve E-90783813-199-16517 sayılı yazı.

KTÜ – Sosyal Bilimler Enstitüsü Batı Dilleri ve Edebiyatı Anabilim Dalı öğretim üyesi Doç. Dr. Ali Şükrü ÖZBAY'ın akademik danışmanlığında, Uygulamalı Dil Bilimi Yüksek Lisans Programı öğrencisi 424317 numaralı Atlas KÖROĞLU'nun yürüttüğü "Curation and Development of Domain-Specific Terminology and Study Materials in Academic English Instruction: Maritime Transportation and Management Engineering" başlıklı yüksek lisans tezi kapsamında "Etik Kurul Belgesi" ile ilgili olarak kurulumuza yaptığı başvuru değerlendirilerek uygun bulunmuş ve sonucu Ek'te gönderilmiştir.

İlgili öğrencinin bilgilendirilmesi hususunda gereğini arz ederim.

Prof. Dr. Abdülkadir PEHLİVAN
Başkan

Ek: Toplantı Tutanağı (3 Sayfa)

Bu belge güvenli elektronik imza ile imzalanmıştır.
Doğrulama Kod: 6DBA054C-B6A9-4061-91FE-7FE1BFD6F660 HİZMETE ÖZEL Doğrulama Adres: https://www.turkiye.gov.tr/karadeniz-teknik-universitesi-ebys

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Sayfa 1 / 1

Appendix 2: Volunteer Participant Form

ARAŞTIRMA GÖNÜLLÜ KATILIM FORMU

Bu çalışma, Akademik Amaçlı İngilizce Eğitiminde Alana Özgü Terimlerin ve Çalışma Materyallerinin Derlem tabanlı olarak Geliştirilmesi: Deniz Ulaştırma İşletme Mühendisliği Örneği başlıklı bir araştırma çalışması olup, bu alanda kullanılan en sık kelime, fiil ve sıfatların bulunup çalışma materyali haline getirilmesini amaçlamaktadır. Çalışma, Atlas Köroğlu tarafından yürütülmekte ve sonuçları ile Deniz Ulaştırma İşletme Mühendisliği öğrencilerinin gelişimine ışık tutulacaktır.

- Bu çalışmaya katılımınız gönüllülük esasına dayanmaktadır.
- Çalışmanın amacı doğrultusunda, elden dağıtılan worksheetler aracılığıyla sizden veriler toplanacaktır.
- İsminizi yazmak ya da kimliğinizi açığa çıkaracak bir bilgi vermek zorunda değilsiniz/araştırmada katılımcıların isimleri gizli tutulacaktır.
- Araştırma kapsamında toplanan veriler, sadece bilimsel amaçlar doğrultusunda kullanılacak, araştırmanın amacı dışında ya da bir başka araştırmada kullanılmayacak ve gerekmesi halinde, sizin (yazılı) izniniz olmadan başkalarıyla paylaşılmayacaktır.
- İstemeniz halinde sizden toplanan verileri inceleme hakkınız bulunmaktadır.
- Sizden toplanan veriler belge-dosya şifreleme yöntemi ile korunacak ve araştırma bitiminde arşivlenecek veya imha edilecektir.
- Veri toplama sürecinde/süreçlerinde size rahatsızlık verebilecek herhangi bir soru/talep olmayacaktır. Yine de katılımınız sırasında herhangi bir sebepten rahatsızlık hissederseniz çalışmadan istediğiniz zamanda ayrılabileceksiniz. Çalışmadan ayrılmanız durumunda sizden toplanan veriler çalışmadan çıkarılacak ve imha edilecektir.

Gönüllü katılım formunu okumak ve değerlendirmek üzere ayırdığınız zaman için teşekkür ederim. Çalışma hakkındaki sorularınızı Karadeniz Teknik Üniversitesi Uygulamalı Dilbilim bölümünden Atlas Köroğlu'na yöneltebilirsiniz.

Araştırmacı Adı : Atlas Köroğlu
Adres : Karadeniz Teknik Üniversitesi Batı Dilleri ve Edebiyatı Bölümü
Cep Tel : (+90) 546 137 46 82

Bu çalışmaya tamamen kendi rızamla, istediğim takdirde çalışmadan ayrılabileceğimi bilerek verdiğim bilgilerin bilimsel amaçlarla kullanılmasını kabul ediyorum.
(Lütfen bu formu doldurup imzaladıktan sonra veri toplayan kişiye veriniz.)

Katılımcı Ad ve Soyadı:
İmza:

Appendix 3: Words before being sent to AI

Word	Frequency
Marine	3,218
Datum	1,414
Sensor	944
Offshore	558
DWT (Deadweight Tonnage)	520
Underwater	350
Turbine	306
REM (Remote Environmental Monitoring)	290
Reactor	276
Coastal	256
Autonomous	254
Industrial	248
Measurement	232
Fuel	228
Connector	202
Buoy	202
Operational	194
Array	188
Tidal	170
Forecasting	170
Subsea	168
Propulsion	160
Platform	158
Deploy	148
Schematic	144
Acoustic	142
Maintenance	140
Configuration	140
Cable	136
Stem	136
Navigation	130
Optical	129
Torque	127
Analyze	124

Appendix 3: (Continued)

Robotic	124
Pipeline	120
Cr (control room)	120
Competence	118
Magnetic	116
Manufacturer	114
Linear	114
Gear	112
Vertical	110
Simulation	110
Calibration	108
Utilize	106
Voltage	106
Regression	104
Deepsea	102
Install	98
Observation	96
Diesel	96
Density	90
MRE (Marine Renewable Energy)	86
Spatial	86
Novel	86
Module	84
MG (Magnetic Gears)	84
Rov (Remotely Operated Vehicle)	82
Storage	80
Salinity	80
Propeller	80
Collision	78
Lidar (Light Detection and Ranging)	76
Radar	74
Aquaculture	74
Grid	74
Fluid	72

Appendix 3: (Continued)

Seabed	70
Transformer	70
Seafarer	70
Tank	68
Mapping	68
Fatigue	68
Trajectory	64
Ferry	64
Tactile	62
Oceanography	62
Turbulence	60
Mooring	56
Naval	52
Velocity	50
Ballast	44
Rotor	28
Accelerate	28
Logistics	28

Appendix 4: Words that were extracted by AI Chatbots

ChatGPT	Extracted Vocabulary
1	Datum
2	Platform
3	Schematic
4	Robotic
5	Competence
6	Linear
7	Utilize
8	Tactile
9	Collision

Microsoft Copilot	Extracted Vocabulary
1	Datum
2	Reactor
3	Operational
4	Forecasting
5	Robotic
6	Competence
7	Linear
8	Utilize
9	Spatial
10	Grid
11	Trajectory
12	Tactile
13	Logistics

Appendix 5: Pre-Test

Pretest

Maritime Transportation and Management Engineering

Name - Surname =

Please write the Turkish definitions of the vocabulary items given in English below. (Please leave the definitions for the vocabulary items you do not know empty).
Lütfen aşağıda İngilizcesi verilen kelimelerin Türkçe karşılıklarını yanlarına yazınız. Bilmediğiniz kelimeleri boş bırakınız.

. Marine =
. Sensor =
. Magnetic =
. Fluid =
. Ballast =
. DWT (Deadweight Tonnage)=
. Trajectory =
. Turbine =
. Simulation =
. Logistics =
. Reactor =
. Acoustic =
. Observation =
. Fuel =
. Platform =
. Measurement =
. Connector =
. Buoy =
. Optical =
. Rotor =
. Array =
. Subsea =
. Collision =
. Propulsion =
. Cable =
. Maintenance =
. Configuration =
. Stem =
. Navigation =
. Pipeline =

. Gear =
. Calibration =
. Regression =
. Deepsea =
. Mooring =
. Cr (control room) =
. Density =
. Seafarer =
. Salinity =
. Storage =
. Propeller =
. Radar =
. Seabed =
. Tank =
. Mapping =
. Oceanography =
. Manufacturer =
. Turbulence =
. Naval =
. Velocity =
. Torque =
. Ferry =
. Module =
. Deploy =
. REM (Remote Environmental Monitoring) =
. Grid =
. Analyze =
. Switchgear =
. ROV (Remotely Operated Vehicle) =

. Diesel =
. Autonomous =
. Fatigue =
. Transformer =
. Install =
. Accelerate =
. Lidar (Light Detection and Ranging) =
. Vertical =
. Forecasting =
. Offshore =
. Aquaculture =
. Novel =
. Underwater =
. MRE (Marine Renewable Energy =
. Spatial =
. Coastal =
. Industrial =
. Operational =
. Voltage =
. Tidal =
. Schematic =

Appendix 6: Post-Test

Post-test

Maritime Transportation and Management Engineering

Name - Surname =

Please write the Turkish definitions of the vocabulary items given in English below. (Please leave the definitions for the vocabulary items you do not know empty).
Lütfen aşağıda İngilizcesi verilen kelimelerin Türkçe karşılıklarını yanlarına yazınız. Bilmediğiniz kelimeleri boş bırakınız.

. Marine =
. Fluid =
. Ballast =
. DWT (Deadweight Tonnage)=
. Trajectory =
. Logistics =
. Acoustic =
. Observation =
. Platform =
. Measurement =
. Connector =
. Buoy =
. Optical =
. Rotor =
. Array =
. Subsea =
. Collision =
. Propulsion =
. Maintenance =
. Configuration =
. Stem =
. Navigation =
. Pipeline =
. Vertical =
. Calibration =

. Regression =
. Deepsea =
. Mooring =
. Cr (control room) =
. Density =
. Seafarer =
. Salinity =
. Tidal =
. Propeller =
. Seabed =
. Tank =
. Mapping =
. Spatial =
. Manufacturer =
. Turbulence =
. Transformer =
. Module =
. Torque =
. Ferry =
. Velocity =
. Deploy =
. REM (Remote Environmental Monitoring) =
. Grid =
. Switchgear =
. ROV (Remotely Operated Vehicle) =

. Diesel =
. Autonomous =
. Fatigue =
. Naval =
. Install =
. Accelerate =
. Lidar (Light Detection and Ranging) =
. Gear =
. Forecasting =
. Offshore =
. Aquaculture =
. Novel =
. Underwater =
. MRE (Marine Renewable Energy) =
. Oceanography =
. Coastal =
. Industrial =
. Operational =
. Storage =
. Schematic =

Appendix 7: Vocabulary Definitions

Maritime Transportation and Management Engineering Vocabulary definitions **SET 1**
Marine = Denizle ilgili / Denizcilikle ilgili *Deniz taşımacılığı, liman işletmeciliği ve deniz çevresiyle ilgili tüm faaliyetleri kapsayan terim.*
Fluid = Sıvı / Akışkan *Denizcilik mühendisliğinde, gemilerde taşınan sıvı ve gazlar; akışkanlar mekaniği, denizcilik uygulamalarında önemli bir yer tutar.*
Ballast = Toprak Yükü / Ağırlık *Gemilerin dengeyi sağlamak için taşıdığı ekstra yük; gemi, yük taşımada dengesini korumak ve derinliğini ayarlamak için balast kullanır.*
DWT (Deadweight Tonnage) = DWT (Ölü Ağırlık Tonajı) *Bir geminin, güvenli bir şekilde taşıyabileceği toplam ağırlık (yük, yakıt, su, mürettebat vb.) kapasitesi.*
Trajectory = Yörünge / İzlenen rota *Bir geminin deniz üzerindeki izlediği yol veya rota; genellikle navigasyon ve rota planlamasında kullanılır.*
Logistics = Lojistik *Yük taşımacılığı, depolama, dağıtım ve tedarik zinciri süreçlerinin planlanması ve yönetimi.*
Acoustic = Sesle ilgili *Sualtı haberleşme ve izleme sistemlerinde kullanılan ses dalgalarıyla ilgili teknolojiler.*
Observation = Gözlem *Deniz trafiği, hava durumu, deniz durumu gibi unsurların izlenmesi ve raporlanması süreci.*
Platform = Platform *Deniz yüzeyinde veya deniz altındaki yapılar; özellikle offshore (açık deniz) operasyonlarında kullanılan petrol ve gaz çıkarma platformları.*
Measurement = Ölçüm *Derinlik, sıcaklık, hız gibi denizcilikte önemli verilerin hassas olarak belirlenmesi süreci.*
Connector = Bağlantı Elemanı *Denizcilik mühendisliğinde, gemilerde veya deniz altı altyapılarında boru hatları, kablolar veya sistemler arasında bağlantı sağlayan elemanlar.*
Buoy = İskele / Deniz Feneri *Gemi seyir güvenliğini sağlamak için su yüzeyinde yüzen, genellikle işaretleme amaçlı kullanılan cihazlar; denizcilik için yönlendirme işareti olarak kullanılır.*
Optical = Optik *Fiber optik kablolar veya optik sensörlerle iletişim veya veri toplama sistemlerini ifade eder.*

Appendix 7: (Continued)

Rotor = Döner parça *Genellikle pervane sistemlerinde veya türbinlerde dönerek enerji üreten mekanik bileşen.* **Array = Dizi / Sistem dizilimi** *Gemiye entegre edilen sensör, radar veya iletişim sistemlerinin belirli bir düzende yerleştirilmiş hali.*
Subsea = Denizaltı *Deniz yüzeyinin altındaki alan; denizaltı mühendisliği, deniz tabanı araştırmaları ve denizaltı altyapılarının inşa edilmesinde kullanılan terim.*
Collision = Çarpışma *Gemi ile başka bir gemi, rıhtım ya da sabit cisim arasındaki istemsiz ve çoğunlukla zarara yol açan temas.*
Propulsion = İtme / Sevk sistemi *Geminin ileri hareketini sağlayan motorlar, pervaneler veya diğer mekanizmalar.*
Maintenance = Bakım / Onarım *Geminin donanımının çalışır durumda tutulması için yapılan düzenli kontroller ve onarımlar.*
Configuration = Yapılandırma / Düzenleme *Gemi üzerindeki sistemlerin (örneğin radar, motorlar, ağ sistemleri) teknik yerleşimi ve ayarları.*

Appendix 8: Image Matching

1- *Match the terms with the images given below.*

a) Fluid **b)** Ballast **c)** Platform **d)** Connector **e)** Buoy **f)** Subsea

…..

…..

…..

…..

…..

…..

Appendix 9: Word Matching

2- *Match the terms with their definitions.*

a) Marine	Lojistik
b) DWT (Deadweight Tonnage)	İtme / Sevk sistemi
c) Trajectory	Ölü Ağırlık Tonajı
d) Logistics	Yapılandırma / Düzenleme
e) Acoustic	Deniz/Denizcilikle ilgili
f) Observation	Dizi / Sistem dizilimi
g) Measurement	Döner Parça
h) Optical	Yörünge / İzlenen rota
i) Rotor	Gözlem
j) Array	Çarpışma
k) Collision	Sesle ilgili
l) Propulsion	Bakım / Onarım
m) Maintenance	Optik
n) Configuration	Ölçüm

Appendix 10: Fill in the Blanks

3- *Fill in the blanks with the words given below.*
marine, fluid, ballast, DWT, trajectory, logistics, acoustic, observation, platform, measurement, connector, buoy, optical, rotor, array, subsea, collision, propulsion, maintenance, configuration
a) The __________ system helps the ship remain stable by adjusting the weight distribution using water tanks.
b) Understanding __________ dynamics is essential for predicting how liquids move through pipelines and tanks onboard.
c) The vessel has a __________ of 60,000 tons, including cargo, fuel, and crew.
d) The captain adjusted the vessel’s __________ to avoid a nearby storm cell.
e) Effective __________ management ensures that cargo is moved efficiently from port to port.
f) __________ sensors are often used to detect objects or activity underwater using sound waves.
g) Continuous __________ of sea traffic patterns helps improve safety and efficiency in crowded shipping lanes.
h) The oil rig is a floating __________ used for offshore drilling and resource extraction.
i) Accurate depth __________ is necessary before anchoring the vessel in shallow waters.
j) A cable __________ failed, causing temporary loss of power to the communication system.
k) A weather __________ was deployed to collect environmental data near the shipping route.
l) The team used __________ fiber cables to enhance the speed of underwater data transmission.
m) The wind turbine’s __________ converts wind energy into mechanical force.
n) The research vessel is equipped with an __________ of sensors to monitor oceanographic conditions.
o) __________ operations often require specialized equipment to operate at great depths below the sea surface.
p) The ship was damaged in a minor __________ with a docked vessel during mooring.
q) A hybrid __________ system was installed to reduce emissions and improve energy efficiency.
r) Regular __________ of ship machinery prevents unexpected breakdowns at sea.
s) The vessel’s radar __________ had to be adjusted to ensure proper function in dense fog.
t) The team specializes in __________ engineering, dealing with environments and systems at or near the ocean.

Appendix 11. Translation Activities

***4-** Write the English definitions of the words next to them*
Gözlem =
Lojistik =
Dizi / Sistem dizilimi =
Deniz/Denizcilikle ilgili =
Ölçüm =
Yörünge / İzlenen rota =
Yapılandırma / Düzenleme =
Bakım / Onarım =
Optik =
İtme / Sevk sistemi =
Döner Parça =
Ölü Ağırlık Tonajı =
Çarpışma =
Sesle ilgili =

Appendix 12: Questionnaire Questions

Question number	Question
1	Çalışma materyalini ilgi çekici ve Teknik kelime öğretimi açısından faydalı buldunuz mu?
2	Çalışma materyalini kullandıktan sonra teknik kelimeleri anlama düzeyinizin geliştiğini düşünüyor musunuz?
3	Öğrenmekte zorlandığınız kelimeler veya kavramlar oldu mu?
4	Çalışma materyalindeki hangi kelimeleri öğrenmesi daha kolay buldunuz ve neden?
5	Eklemek istediğiniz başka görüş veya yorumlarınız var mı?

Appendix 13: Research Data Entered on Excel

A1 *fx* Participants

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
1	Participan	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q
2	1	0	0	0	0	0	1	1	0	1	0	1	0	1	1	0	0	1	0	0	0	0	1	
3	2	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	
4	3	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	
5	4	0	0	0	0	0	1	0	0	1	0	0	1	1	1	0	1	1	0	1	0	0	0	
6	5	0	0	1	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	1	1	
7	6	0	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	1	0	0	1	
8	7	1	0	1	0	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	0	0	1	
9	8	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	
10	9	0	0	0	0	0	1	0	1	0	0	1	1	0	0	0	1	1	0	0	0	1	1	
11	10	0	0	0	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0	1	0	
12	11	0	0	0	0	0	1	1	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0	
13	12	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
14	13	1	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	1	0	0	1	0	1	
15	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
16	15	0	0	0	0	0	0	1	0	1	0	1	1	1	0	0	1	1	0	1	0	0	0	
17	16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	
18	17	0	0	1	0	0	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0	1	
19	18	0	0	1	0	0	1	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	
20	19	1	1	0	0	0	1	1	1	0	0	1	0	1	0	0	0	0	0	1	0	0	1	
21	20	1	0	0	0	0	1	0	1	1	1	0	1	1	1	0	1	1	0	1	0	1	1	
22	21	0	0	1	0	1	0	1	1	1	1	0	0	1	0	0	0	1	1	1	1	0	0	
23	22	0	0	1	0	0	1	1	1	1	1	1	0	1	1	0	0	1	0	0	0	1	1	
24	23	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	
25	24	1	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	0	1	1	
26	25	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	
27	26	0	0	0	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	0	0	1	
28	27	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	
29	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
30	29	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	
31	30	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	1	1	1	0	1	1	
32	31	1	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	
33	32	1	0	1	0	0	0	0	0	1	1	1	0	1	0	0	0	1	0	1	0	0	0	
34	33	1	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	
35	34	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	
36	35	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	1	0	0	0	0	1	
37	36	0	0	0	0	0	1	1	0	1	0	1	0	1	0	0	0	1	0	0	1	0	1	

Appendix 14: Participant Performances

Participant ID	Total Count Pre-Test	Total Count Post-Test
1	28.00	51.00
2	15.00	31.00
3	12.00	28.00
4	24.00	38.00
5	17.00	44.00
6	24.00	52.00
7	31.00	51.00
8	10.00	16.00
9	32.00	56.00
10	46.00	59.00
11	18.00	31.00
12	12.00	34.00
13	21.00	47.00
14	1.00	15.00
15	22.00	47.00
16	6.00	24.00
17	47.00	61.00
18	19.00	34.00
19	25.00	42.00
20	36.00	66.00
21	25.00	40.00
22	36.00	56.00
23	8.00	24.00
24	14.00	33.00
25	11.00	26.00
26	11.00	18.00
27	8.00	25.00
28	9.00	25.00
29	12.00	26.00
30	19.00	35.00
31	10.00	18.00
32	25.00	41.00
33	15.00	23.00
34	15.00	27.00
35	13.00	26.00
36	29.00	46.00

Appendix 14: (Continued)

37	36.00	58.00
38	21.00	38.00
39	19.00	36.00
40	38.00	57.00
41	16.00	31.00
42	34.00	39.00
43	16.00	26.00
44	19.00	26.00
45	2.00	15.00
46	26.00	62.00
47	9.00	49.00
48	31.00	56.00
49	36.00	42.00
50	10.00	21.00
51	8.00	19.00
52	10.00	28.00
53	9.00	19.00
54	6.00	25.00
55	23.00	50.00
56	17.00	35.00
57	12.00	31.00
58	9.00	29.00
59	20.00	27.00
60	7.00	14.00
61	13.00	20.00
62	8.00	26.00
63	15.00	20.00
64	15.00	28.00

Appendix 15: Question Level Performance

Question number	Pre-test Correct Answers	Post-test Correct Answers	Total Improvement
Q1	14	38	24
Q2	3	38	35
Q3	13	28	15
Q4	1	12	11
Q5	5	13	8
Q6	28	45	17
Q7	35	47	12
Q8	15	21	6
Q9	38	54	16
Q10	18	32	14
Q11	29	43	14
Q12	7	18	11
Q13	51	56	5
Q14	15	27	12
Q15	2	7	5
Q16	8	24	16
Q17	33	46	13
Q18	5	42	37
Q19	14	41	27
Q20	8	19	11
Q21	19	41	22
Q22	39	60	21
Q23	11	23	12
Q24	12	20	8
Q25	31	53	22
Q26	2	31	29
Q27	23	33	10
Q28	6	25	19
Q29	34	56	22
Q30	12	40	28
Q31	13	49	36
Q32	3	46	43
Q33	26	31	5
Q34	39	60	21
Q35	24	42	18
Q36	33	48	15

Appendix 15: (Continued)

Q37	19	54	35
Q38	9	16	7
Q39	14	21	7
Q40	41	58	17
Q41	14	25	11
Q42	17	31	14
Q43	4	7	3
Q44	10	27	17
Q45	4	6	2
Q46	2	7	5
Q47	2	4	2
Q48	9	22	13
Q49	4	24	20
Q50	3	6	3
Q51	24	43	19
Q52	2	19	17
Q53	2	21	19
Q54	24	27	3
Q55	33	31	-2
Q56	3	20	17
Q57	16	23	7
Q58	12	27	15
Q59	37	53	16
Q60	7	15	8
Q61	40	54	14
Q62	36	61	25
Q63	4	13	9
Q64	18	23	5
Q65	12	27	15
Q66	36	39	3
Q67	6	17	11
Q68	25	42	17
Q69	6	21	15
Q70	27	50	23

Appendix 16: Responses Given to the Questionnaire

Participant Number	Question 1	Question 2	Question 3	Question 4	Question 5
1	Evet	Evet	Hayır	Günlük hayatta kullanımı olan kelimeler	Yok
2	Evet	Evet	Bilmediğim şeyler	Hatırlamıyom	Dersleriniz öğreticiydi ama az sayıdaydı hocam herşey için teşekkürler
3	Evet	Evet gelişti	Günlük hayatta karşılaşmadım kelimeler	Kolay kelimeler	Yok
4	Evet	Kesinlikle evet	Bir kaç kelime harici hayır	Propeller ve marine	Hayır yok
5	evet buldum	kelimeleri daha iyi öğrendim	uzun kelimeler	sensor ve turbineyi hatırlıyorum sadece	hayır
6	Kelimeleri güzel öğrettiniz.	Kelimeler ikinci sınavda daha kolaydı.	Bazı tuhaf kelimeler	Kısa ve günlük hayatta gördüğüm kelimeleri	Hayır. Teşekkürler.
7	evet eğlenceli ve güzeldi	Aktivitelerden sonra kelimeleri daha iyi anlayabildim	Fazla değil	Derste önceden gördüğümüz kelimeler	Hayır yok
8	Evet guzel ve egiticiydi	Evet	Scematik	Sensör ve radar.	
9	evet	evet	evet	hepsi	hayır
10	Evet faydalı ve ilgi çekiciydi	Evet	Uzun olan birkaç tanesi	Basit olanlar	Hayır
11	Buldum	Evet gelisti	Hayir	Cogunu	
12	Evet	Evet	Evet	Evet	Yok
13	evet	evet	bazen	hepsini	hayır
14	Evet	Evet	Hayır	Kolay da değildi zorda normaldi	Yok
15	Evet	Evet	bir kaç	.	
16	evet	evet	bazı kelimelerde oldu		hayır
17	Evet	Evet	Hayır	Meslek ile Alakalı terimleri	Hayır

Appendix 16: (Continued)

18	Evet	Evet	Evet	Fiilleri	Yok
19	evet	evet	evet		hayır
20	Evet	Evet	Evet		Yok
21	evet faydalı buldum.	evet düşünüyorum. çalıştıkça gelişiyo	hayır olmadı.		
22	Evet	Evet	Hayır	Evet çünkü iyi açıklanmışlar	Yok
23	Evet	Evet	Hayır	Evet çünkü çok iyi acıklanmıştılar ekstra bir yardımla oldukça anlaşılır şekilde oldu	Hayır
24	Evet	Kesinlikle	Hayır	Denizcilik ingilizcesi	Hayır yok
25	Evet	Evet kesinlikle	Hayır	Hepsi çok öğreticiydi	Teşekkürler
26	Evet	Evet	Hayır		
27	Evet	Evet	Hayır	Yok	Yok
28	Evet	Evet	Hayır	Hepsini öğrenmesi kolaydı	Yok
29	Evet	Bunun için daha çok pratik yapmam lazım.	Hayır	Daha önceden aşina olduğum kelimeleri öğrenmek daha kolay oldu.	
30	Evet	Evet	Hayır	Hepsi	
31	Evet	Evet			
32	Evet	Evet	Evet		
33	evet	evet	hayır	.	.
34	Evet	Düşünüyorum	Olmadı	Teknik kelimeleri	Yok
35	Evet	Evet	Hayır		Yok
36	Evet	Evet, düşünüyorum.	Hayır, gayet açık ve anlaşılırdı.	Tamamı öğrenmesi kolay ve anlaşılırdı.	

CURRICULUM VITAE

Atlas KÖROĞLU completed his bachelor's degree in English Language and Literature at Karadeniz Technical University in 2021. In the same year, he received his sworn translator license. He has been working as an English teacher for three years and has also served as a translator at several international meetings. He is currently pursuing his master's degree in Applied Linguistics at Karadeniz Technical University. Alongside his interest in linguistics, he has a strong enthusiasm for computer science and pursues an associate's degree in Computer Programming.

KÖROĞLU speaks English and French.