Machine Translation: A Study on Turkish-English Translation Assisted by Software

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Submitted to the
Institute of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Master of Technology
in
Information Technology

Eastern Mediterranean University
February 2023
Gazimağusa, North Cyprus

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ABSTRACT

Communication has been a big part of how our species has changed since the beginning of time. So much that today, it is hard to imagine running a business or living a normal life without a language that everyone speaks (Freitag et al., 2021). The use of mechanical dictionaries to bridge the barriers between languages was first suggested in the 17th century (Hutchins & Somers 1992), and these technologies have had a transformative impact on communication, the mode of information sharing and access globally especially with frequent cross-cultural communication among people from countries and regions. Machine translation (MT) is simply automatic translation. Systran (2004) describes machine translation as a process that uses computer software to convert text from one language to another. It is the process of translating words from one natural language such as English to another such as Turkish using computer software. Translation software have gained popularity given that they provide a useful environment to facilitate and manage translation projects.

This research includes a review of existing translation approaches, it sheds light on the current state of machine translation technology and its impact on the translation industry. The study further explores the nature of the translation process assisted by software and implements a model which will be tested from the end user`s perspective for effectiveness using Software Usability Measurement Inventory.

Keywords: MT, Machine Translation, Computer Assisted Translation, Neural Machine Translation, Statistical Machine Translation, Rule-Based Machine Translation, Translation Software, Google Translate.

ÖZ

İletişim, zamanın başlangıcından beri türümüzün nasıl değiştiğinin büyük bir parçası olmuştur. O kadar ki, bugün herkesin konuştuğu bir dil olmadan bir iş yürütmeyi veya normal bir hayat yaşamayı hayal etmek zor (Freitag ve diğerleri, 2021). Diller arasındaki engelleri aşmak için mekanik sözlüklerin kullanılması ilk olarak 17. yüzyılda önerildi (Hutchins & Somers 1992) ve bu teknolojiler iletişim, bilgi paylaşımı modu ve özellikle sık kültürler arası iletişim ile küresel olarak erişim üzerinde dönüştürücü bir etkiye sahip oldu ülkelerden ve bölgelerden insanlar arasında. Makine çevirisi (MT), basitçe otomatik çeviridir. Systran (2004), makine çevirisini, bir dildeki metni diğerine dönüştürmek için bilgisayar yazılımına eşlik eden bir süreç olarak tanımlamaktadır. İngilizce gibi bir doğal dilden Türkçe gibi bir başka dile bilgisayar yazılımları kullanılarak kelimelerin çevrilmesi işlemidir. Çeviri yazılımları, çeviri projelerini kolaylaştırmak ve yönetmek için kullanışlı bir ortam sağladıkları için popülerlik kazanmıştır.

Bu araştırma, mevcut çeviri yaklaşımlarının bir incelemesini içerir, makine çevirisi teknolojisinin mevcut durumuna ve bunun çeviri endüstrisi üzerindeki etkisine ışık tutar. Çalışma, yazılımın desteklediği çeviri sürecinin doğasını daha da araştırıyor ve Yazılım Kullanılabilirlik Ölçümü Envanteri kullanılarak son kullanıcının bakış açısından etkinliği test edilecek bir model uyguluyor.

Anahtar Kelimeler: MT, Makine Çevirisi, Bilgisayar Destekli Çeviri, Sinirsel Makine Çevirisi, Istatistiksel Makine Çevirisi, Kural Tabanlı Makine Çevirisi, Çeviri Yazılımı, Google Çeviri.

DEDICATION

Dedicated to the memory of my late father, Saliu A. Ismaila. I am forever grateful for his unwavering support and the time I was able to spend with him. I will always remember his wise words and guidance as I navigate through life.

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my mother, for her love, support, and encouragement throughout my studies. Her unwavering belief in me and her constant encouragement have been a source of strength and inspiration. I could not have come this far without her prayers, love, and guidance.

To my friends and family (home and abroad), who have been my support system throughout this journey, I am truly grateful. Their unwavering support, encouragement and understanding have been invaluable to me. I thank them for their patience, love and for always being there for me.

Finally, I would like to express my appreciation to my thesis advisor, Asst. Prof. Dr. Mustafa Tanel Babagil for always being available whenever I needed him and giving me the guidance and support, I needed throughout my research.

To all of you, I am truly grateful for your love, support and for making this journey a memorable one.

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LIST OF ABBREVIATIONS

CAT	Computer Assisted Translation
DMT	Direct Machine Translation
EMU	Eastern Mediterranean University
HAMT	Human-Aided Machine Translation
L1	First Language
L2	Second Language
MART	Machine-Aided Human Translation
MT	Machine Translation
RBMT	Rule-Based Machine Translation Approaches.
SL	Source Language
SMT	Statistical Machine Translation
TL	Target Language

Chapter 1

INTRODUCTION

The field of Machine Translation (MT) has gained significant attention in recent years, particularly with the proliferation of free online MT tools like Google Translate (GT). Advances in Artificial Intelligence have led to a significant improvement in the quality of translations provided by these tools. Google Neural Machine Translation (GNMT), introduced in 2016, is a notable example of this progress. GNMT encodes phrase semantics, rather than relying on memorized phrase-to-phrase translation, allowing it to gain knowledge from the numerous examples available online and produce superior translations (Schuster et al., 2016). Even when students use MT to help them with vocabulary research and coursework, teachers are worried about the potential negative consequences this has on their students' language development and academic honesty. New research emphasizes the need to stop criticizing the use of MT and instead teach students how to utilize it effectively and ethically in their language study (Ranathunga, et al, 2021).

Thanks to advancements in artificial intelligence, language and translation technologies have advanced greatly in this era of technological advancements. These days, everyday communication is made easy and fast with free online translation tools like DeepL-translate, and Google-translate, which allow users to easily bypass language barriers and get translations. Technology is becoming increasingly important in the translation business. According to Doherty et al. (2018), customers are asking for machine translation to be increasingly used in translation projects. Given this scenario, there is a growing sentiment that students and graduates in the field of translation should be more educated in computer-assisted translation (CAT) and related technologies, like machine translation (MT) and translation memories (TM), in order to facilitate the longevity and strength of the profession. However, many disagree with this strategy, citing concerns about MT's lack of detail, precision, and human redundancy. Landauer, (1988) stated that in spite of the benefits and popularity of MT in the translation industry, it is unrealistic to expect 100% accuracy without further human review of issues such as cultural fit and residual typos. Research suggests that translators do not need to have experience with MT to work for international organizations.

Communication has been a major part of how our species have changed since the beginning of time. Today, it is difficult to imagine running a business or living a normal life without a language that everyone speaks (Freitag et al., 2021). Language translation can be done by a person, but this is costly and not always possible (Fan et al., 2014). This barrier can be overcome by automating the translation process, which is what machine translation does. This change is very important because it makes it easier for different people to talk to each other and provides the same access to information. Accordingly, the idea of customizing machine translation tools by human translators, or perhaps the process of doing so, is a recent concept that needs to be clarified, even though research on automatic translation systems has been ongoing for a long time. According to Specia et al., (2018) MT, as it is more commonly known, is a difficult procedure that falls between conventional editing and translation from scratch. The effectiveness of MT is influenced by both internal and external factors, such as the calibration of the machine translation engine, the technical proficiency of the human translator, or the language pair employed (Cadwell et al., 2018).

1.1 Statement of Research Problem

In the 17th century, it was first proposed to employ automated means to break down language barriers (Hutchins & Somers 1992), and has had a transformative impact on communication, the mode of sharing information, and access globally, especially with frequent cross-cultural communication among people from different countries and regions. For cross-language information conversion, relying only on manual translation by human experts is no longer sufficient to meet social development needs. This is primarily because machine translation software (MTS) is much faster than human translation. Systran (2004) describes machine translation as "a process that utilizes computer software to convert text from one language to another”. It entails using automated means to translate from one natural language, such as English, to another, such as Turkish. It has become increasingly popular as it offers a useful environment for efficiently organizing and carrying out translation projects. In this study, we explore the usage, challenges, and reliability of using translation software for communication and information gathering by students in Eastern Mediterranean University.

1.2 Objectives of the Research

To understand MT adoption and use, this study identifies the perceived qualities (learning, efficiency, affect, control, and helpfulness) of these tools. The objectives are as follows.

(a) To examine the impact of MT usability on the “learnability” of MT tools.

(b) To examine the impact of MT usability on the “efficiency” of MT tool usage.

(c) To examine the impact of MT usability on the “affect” of MT tool usage.

(d) To examine the impact of MT usability on the “control” of the usage of MT tools.

(e) To examine the impact of MT usability on the “helpfulness” of the usage of MT tools.

1.3 Research Questions

The study questions include:

(a) What impact does MT usability have on MT tool usage learnability?

(b) To what extent does MT usability influence MT tool efficiency?

(c) To what extent does MT usability affect MT tool use?

(d) To what extent does MT usability control MT tool use?

(e) To what extent does MT usability influence MT tools’ helpfulness?

1.4 Definitions of Terms

CAT: Computer Aided Translation. “Any type of computerized tool that translators use to help them conduct their jobs” (Bowker 2002).

MT: Machine Translation. Defined by Doug Arnold et al. (1994) as “the attempt to automate all, or part of the process of translating from one human language to another.”

1.5 Assumptions

For the purpose of this study, it is assumed that students at EMU are computer literate, have Internet-enabled devices, and have experience in the use of MTS.

1.6 Delimitations and Limitations

This study focuses exclusively on digital text. The specifics of how paper documents can be input into computers or how computers can understand spoken language were not covered in this study. Respondents' busy schedules may represent a barrier; therefore, obtaining questionnaire response on time may be difficult. Furthermore, the researcher used the MTS to translate the questions from English to Turkish, allowing students who did not speak English to participate in the study. The researcher also enlisted the help of the MTS in translating the responses he received from such people back into English. It is possible that vocabulary may have been lost during the translation process. Finally, the researcher was constrained to rely on the data provided by the research participants and was unable to evaluate the reliability and accuracy of the information.

1.7 Importance of the Study

The study provides an analysis of the nature of CAT use in translation and MTS usage among EMU students. This provides motivation for future researchers from various fields to delve deeper into various subtle concepts within their respective areas of study. Different levels of proficiency in learning new languages react differently to the introduction of the MT. Research has shown that MT can improve students' writing abilities. Lee et al. (2020) evaluated the original writing of students for whom English was a second language, against the revised version that had been machine-translated. They found that through revisions, students were able to improve their writing grades and reduce lexical and grammatical errors.

1.8 Thesis Outline

This thesis comprises five chapters. The first chapter provides an introduction to MT and MTSs. It explains the topic to be investigated, its significance, and the aims and objectives of the research goal. The second chapter presents an in-depth overview of prior empirical and theoretical literature on MT usability, as well as the influence of MT usability on the perceived quality of MT adoption. The methodology used in this study is discussed extensively in Chapter 3, including the data collection, population sampling, instrument validation, and data analysis procedures. Chapter 4 presents the hybrid machine model. Chapter 5 covers the data analysis and results of the study. Chapter 6 presents the conclusions, recommendations, implications, limitations, and areas for future research.

Chapter 2

LITERATURE REVIEW

Upon examination of the research on CAT and MT tools, it was discovered that a significant number of studies on this topic have been conducted in places where English is not the primary language of instruction. Review also shows that previous studies on computer-assisted translation (CAT) have investigated the benefits of CAT, factors influencing the use of computers in translation, the limitations of CAT, and recent advancements in this field.

Learning a language has undergone a radical digital revolution in the 21st century. The shift has allowed students to gain access to cutting-edge digital resources and boost productivity (Huang et. al., 2021). The digital transformation's key technology, artificial intelligence (AI), has been applied to the field of language education. Immersing pupils in digital environments, such as those provided by VR and AR software, has been shown to be effective for teaching and learning foreign languages (Muftah et al., 2022). Artificially intelligent chatbots were used as practice conversation partners in language classes. MT is one developing technological area that has altered traditional instructional practices (Loock R et al., 2020). The term "machine translation" is used to describe the method by which documents in one natural language are automatically translated to another using a computer and appropriate software. There are three different kinds of MT: statistical MT (SMT), neural MT (NMT), and rule-based MT (RBMT). The quality of translations has greatly increased since NMT was introduced and Google's NMT algorithm was made public in 2016. There has been a meteoric rise in the variety of translation platforms that include NMT since then (Vieira et al., 2020).

MT has made significant contributions to the teaching of a number of disciplines in higher education, including the medical, scientific, and linguistic professions. Users in the nursing field have seen benefits from using MT systems as it has improved their capability to read and understand scholarly literature from all over the world (Matusiak et al., 2020). Biology and microbiology students frequently use MT resources to facilitate their bilingual learning in university-level science courses. Furthermore, MT is useful as an instructional tool in L2 writing, and the assessment metrics are thought to be reliable in judging the quality of student translations and interpretations. There have been reports of issues arising from the use of MT technologies in online collaborative writing projects involving students (Bowker, 2020). Privacy, academic integrity, the possibility of Systemic bias in AI, understanding of diverse devices, understanding of various translation tasks, and improving the output through editing the input are the six components of MT knowledge that Bowker underlined. Additionally, creativity in translation may play a vital role in stimulating students' interest in reading in a second language (Bowker et al., 2019).

2.1 Historical Development of MT

As the world emerged from the aftermath of World War II, the field of machine translation began to take shape and evolve. Early efforts involved programming computers to utilize grammar rules and search for terms in large multilingual glossaries (Hutchins & Somers, 1992). Despite initial efforts, the rule-based method of machine translation proved to be a flop, with translations lacking the finesse and precision of a skilled human translator, resulting in little practical use. In 1933, George Artsrouni, a French-Armenian, filed two patents for a paper tape storage device that could be used to find the equivalent of any word in another language (Mohammed, Samad & Mahdi 2018). With the advent of the first computer in 1946, attempts were made to use it for language translation through the creation of computer tools that can translate a variety of documents from one language to another (Mohammed et al 2018). In 1949, Weaver proposed the MT system, and Georgetown University conducted the first MT trial in 1954.

The ALPAC Report from the United States in 1965 ushered in MT's dark period. The Automatic Processing Advisory Committee (ALPAC) raised well-known concerns that machine translation is less efficient, slower, and more costly than human translation. Additionally, the report aimed to show that there is no justification for investing in research in machine translation. Nonetheless, vast accomplishments in MT studies were seen in France, Germany, Canada, America, and the CEC, among others. In 1995, Hutchins opined that Japan had the most commercial activity for almost all computer companies in the 1980s. This was due to the creation of a Japanese to English MTS and the 1981 implementation of the ALPS systems, which is considered to be the first CAT system, a turning point in the history of CAT (Mohammed et al., 2018). Makin (2003) noted that it was a significant advancement over earlier work that employed statistical methods that began in the late 1980s, as researchers and engineers abandoned the old, rigid rule-based approach and embraced a more dynamic statistical method, using vast amounts of text and examples as the foundation for translation.

The idea of a machine that could translate one natural language to another was first imagined in the 17th century, but it wasn't until the latter half of the 20th century that it became a reality. Machine translations, while providing a useful tool, are not perfect, as it is an ideal that even human translators cannot achieve (Gally, 2018). Furthermore, Machine Translation Systems (MTS) are not suitable for translating literary texts as the intricacies and subtleties of poetry are beyond the scope of computational analysis. The translations produced by MTS are mainly used for technical manuals, scientific documents, commercial prospectuses, administrative memoranda, and medical reports (Tobin, 2015). The primary objective of the field of machine translation is not to conduct theoretical or academic research, but rather to apply the fields of computer science and linguistics to the development of systems that can meet practical needs. The Automatic Language Processing Advisory Committee (ALPAC) report of the 1960s was a pivotal moment, shifting the tide of the field's development. The late 1970s saw a resurgence of interest in machine translation, leading to the birth of commercial systems in the 1980s. The 1980s and 1990s were a time of continued research and innovation, resulting in a surge of adoption and usage of machine translation systems (Sommers, 1992).

Translating works of literature, legal documents, and many branches of sociology are more "culture-bound," therefore scholars have focused almost solely on translating scientific and technical documents from the start (Hutchins, 1995). The demand for translation in the fields of science and technology has virtually always outstripped the capacity of the translation profession, and this trend is only expected to accelerate. Furthermore, instantaneous online translations are now required because of the internet, and human translators cannot fulfill this necessity. There are two main types of demand for this. Translations that are considered "publishable" have been necessary for a long time, especially for the creation of multilingual materials for big companies (Briggs, 2018). In such cases, the output of MT systems can be beneficial by providing rough translations that can be edited before publishing, this type of translation is referred to as "human-aided machine translation". Nonetheless, we do not often require a version that is "completely" accurate, but rather one that can be created quickly (often right away) and conveys the primary idea of the original text, regardless of how poor the syntax, vocabulary, or style may be. This type of machine translation is frequently referred to as "machine translation for assimilation," as opposed to "machine translation for dissemination," which refers to the process of producing translations that are sufficiently accurate to be published. More recently, a third application for MT in social situations (email, chat rooms, etc.), where high quality is not required, has been discovered, and is termed "machine translation for communication" (Hutchins, 1995).

2.2 Competence of MT

CAT tools have grown in popularity as a helpful environment for organizing and carrying out translation projects. Translators use them to boost output while keeping top-notch translation services. In a study on the consequences of globalisation on cross-cultural communication, Lowel and Thakkar (2012) found that to accomplish the organisation’s objective and produce value for stakeholders, global organisations must understand how to interact with employees and consumers from diverse cultures. They also recognised the importance of technology in how firms communicate globally and sell their goods and services. Doherty (2016) stated that technological advancements have resulted in unprecedented changes in translation due to interlingual communication, and the use of CAT and MT tools, in particular, has increased translation productivity, quality, and supported international communication. However, the tools have their own set of issues, such as quality concerns, misrepresentation, and overuse.

Translating involves recreating a message in a target language, making sure it holds context. The objective is to reach semantic equivalence and language appropriateness in the translated text (Nida and Taber, 1996). It can be argued that translating alone is enough, which is the modification of a form of language into another language (target language) while keeping the equivalence of all its elements, including phrases, sentences, paragraphs, and others, both oral and written. The word possibilities available in any language are numerous but limited, posing a communication issue regarding proper word selection (Chiaro, 2008). These words are then put together by language, which has rules that make it hard for the speaker to say what he wants to say. Thus, the speaker's encoding process presents unique difficulties in transmitting his thought to the listener. As a result, the speaker's thoughts are limited by linguistic constraints, and the encoded information is merely a rough approximation of his or her thinking.

2.3 What is Machine Translation?

The phrase "machine translation" (MT) refers to the use of computer systems to produce translations, with or without the assistance of human translators (Hutchins et al., 1995). In simpler terms, translating is an attempt to transfer the message of the source language into a language that is equivalent to it (Newmark, 1988). The differences between MART and HAMT are not always conclusive, and the term "CAT" can refer to either. However, the key aspect of machine translation (MT) is the automation of the entire translation process, and this is its defining characteristic (Kamakshi, 2008). The capabilities of MT are not restricted to simple word-for-word translations. They are also able to work on translations of spoken words. It is believed that more than 1000 different kinds of translation software, both online and offline, are available for commercial use on the global market (Doherty & Kenny, 2014). A good number of them are available at no cost for use.

2.4 Machine Translation on the Internet

The Internet has played a significant role in the advancement of Machine Translation (MT) since the mid-1990s. To begin with, there has been a rise in MT software products specifically designed for offline translation of web pages and e-mails. While Japanese companies were the first to venture into this field, competitors soon followed suit globally. Secondly, starting from the mid-1990s, a considerable number of MT vendors began providing online translation services that could be accessed on-demand via the internet. Systran is considered the first service of this kind (Gaspari, 2004). Soon after, the renowned translation service Babelfish was launched on the AltaVista website, offering translations from French, German and Spanish to and from English using Systran. This was followed by a plethora of other online services, most of which were offered to users at no cost (Gaspari, 2004 and Hutchins, 2007).

It is evident that the translations produced by online MT services can often fall short of perfect. Nevertheless, it's undeniable that these services are catering to a significant demand for swift, rough translations into users' native languages for general understanding. This fulfils the same function that was provided by mainframe systems in the 1960s, which was often overlooked at the time and in the years that followed. Researchers in the field of machine translation have generally ignored online MT services notwithstanding their extensive use and evident impact on the public 'image' of MT (often negatively) (Gaspari, 2004).

As a result of the widespread availability of Internet access, less reputable businesses have begun marketing online electronic dictionaries (or phrase books) under the guise of "translation systems." Anyone utilizing such a software to translate entire sentences (or even paragraphs) is likely to be disappointed with the results, even if they themselves do not understand the target languages (Hutchins, 2007).

2.5 Machine Translation Approaches

MT systems are able to be categorized based on the primary approach they employ. These approaches includes rule-based machine translation (RBMT) approach, corpus-based machine translation approach and hybrid machine translation approach The rule-based approach and the corpus-based approach. These approaches are described further below.

2.5.1 Rule-Based Machine Translation Approaches (RBMT)

Rule-Based Machine Translation, also referred to as the Classical Approach to Machine Translation, is a methodology that encompasses the utilization of linguistic information about the source and target languages in machine translation systems. This information is primarily sourced from bilingual dictionaries that encapsulate the primary semantic, morphological, and syntactic patterns of each language. A RBMT system inputs a source language, and based on morphological, syntactic, and semantic analysis of both the source and target languages, it outputs a translation in the target language, specific to the given translation task (Mukta et al., 2019; Sghaier & Zrigui, 2020). The RBMT methodology employs a collection of language norms across three distinct stages: analysis, transfer, and generation. As a result, the following components are necessary for a rule-based system: analysis of syntax and semantics, generation of syntax and generation of semantics. Also, RBMT source text produces a target text by following the procedures that are outlined in the following.

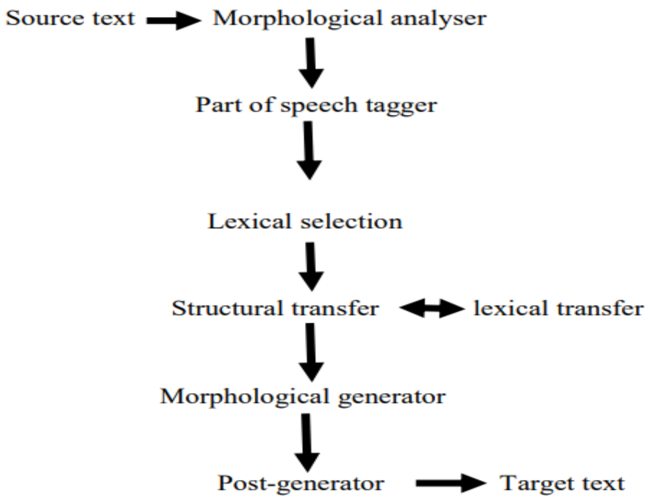

Figure 2.1: Architecture of the RBMT Approach (Source: Wikipedia)

The fundamental strategy of RBMT systems is to link the format of the sentence that is provided as input with the structure of the phrase that is required as output, while ensuring that each sentence maintains its original meaning (Ashraf, 2015). The RBMT approach is plagued with a number of difficulties, including the ones listed below:

i. A shortage of really excellent dictionaries in the available quantity: Creating brand new dictionaries is an expensive endeavor.

ii. There are still some linguistic details that require manual configuration.

iii. It can be challenging to navigate the ambiguity, rule interactions, and idiomatic expressions that come with large-scale systems.

iv. Inability to successfully transition to new domains. Although RBMT systems typically offer a mechanism to generate new rules, as well as to extend and modify the lexicon, making changes to such a system is typically very expensive, and the outcomes frequently do not justify the costs.

2.5.1.1 Approach Based on Direct Machine Translation (DMT)

The Direct Machine Translation Approach represents the initial, most fundamental step in the translation process. It is located at the base of the pyramid. The DMT approach is the one that has been around the longest but is the least used (Navigli & Ponzetto, 2012). The translation is done word for word in direct translation. Machine translation systems that take this strategy are able to translate source language (SL), directly into the target language (TL). The literal meanings of the words spoken in the SL are conveyed without the use of any additional or intermediary representations (Chen, Y., Peng, Zhu, & Li, 2020). The analysis of texts written in SL is focused on just one TL at a time. Systems that use direct translation are typically bilingual but only work in one direction. When using this approach, only a small amount of syntactic and semantic scrutiny is required. It is possible to describe it as a "word-for-word" translation, although there may be some adjustments made to the original word structure (Okpor, 2014). It produced translations of the caliber that might be expected from someone with only rudimentary familiarity with the grammar of the target language and a meager bilingual dictionary. This method also suffers from a lack of linguistic and computational sophistication. From a linguistic standpoint, what is required is an examination of the source text's internal structure, in particular the grammatical links between the sentences' key components (Yates, 2006).

2.5.1.2 Approaches Based on Interlingual Machine Translation

This is one example of a rule-based approach to machine translation. The Interlingua-based MT system begins with the source text, which it then turns into an intermediate representation known as Interlingua. The final step is to translate the Interlingua representation into the required target text. Due to the fact that Interlingua is not dependent on any one language, it can play an important part even if the number of target languages expands. This is one of the most significant benefits offered by Interlingua (AlAnsary, 2014). The ineffectiveness of the systems of the first generation resulted in the creation of increasingly complex linguistic models for use in the translation process. As the field of Machine Translation progressed, support grew for a more nuanced approach. One that involved breaking down the source language text into an intermediary representation, serving as the foundation for generating the text in the target language. This representation would be a reflection of the text's "meaning" in some form (Myles, 2002).

A significant gain of utilizing this technique is the fact that the interlingua will accrue a greater value as the number of target languages into which it can be translated grows. Still, the KANT system (Nyberg & Mitamura, 1992) is the sole interlingual machine translation tool to have been commercially deployed. This system is intended to convert Caterpillar Technical English (CTE) to different languages and has been made available for purchase. The challenges of an Approach Based on Interlingual Machine Translation - Even for languages that are closely linked to one another, such as the Romance languages (French, Italian, Spanish, and Portuguese), it can be challenging to define what exactly constitutes an interlingua. Linguists have worked tirelessly over the years to develop a truly "universal" and language-independent interlingua; yet, they have been unsuccessful. To make the intermediate representation, it is hard to get meaning from texts in their original languages and semantic differentiation is unique to the target language, and making such distinctions is like transferring words from one language to another (Dorr, 2004).

2.5.1.3 Transfer-based Machine Translation Approach

To address the limitations of direct translation, the transfer-based method was created. This method is split down into three distinct steps. In the first phase, termed analysis, the syntactic structure of the original text is examined. The second stage is termed transfer, and in this stage, the syntax of the source text is converted into the syntax of the destination text. Syntactic structure of the target text is used to construct the target text in the third stage, called generation (Khana, 2021).

Due to the shortcomings of the Interlingua technique, a superior rule-based translation strategy known as the Transfer-based Approach was eventually found. Transfer-based MT is analogous to multilingual MT in the sense that It generates a translation from a representation that closely resembles the meaning of the sentence being interpreted (Sans, 1998). The final step of this translation approach involves the utilization of a TL morphological analyzer in order to produce the final texts in the TL. This method of translation makes it feasible to generate translations of a decently high quality, with an accuracy of somewhere in the neighborhood of 90%. The challenges of Transfer-based Machine Translation include complete as much work as feasible in reusable modules of analysis and synthesis can be a challenging endeavor and the challenging to maintain the maximum level of simplicity in transfer modules (Sánchez-Martínez, 2008).

2.5.2 Corpus-Based Machine Translation Approach

A different approach to MT, Corpus-based MT, also referred to as data-driven MT, is an alternative approach for machine translation that was created to resolve the issue of information intake that affects RBMT. Corpus-Based Machine Translation (CBMT) is a translation method that, as its name suggests, gathers information from a multilingual parallel corpus in order to produce new translations. This strategy makes use of a substantial quantity of unprocessed data in the form of parallel corpora. Text and their respective translations are included in this raw data set. Specifically, there are two types of corpus-based methods (Comparin, 2017): the approach of statistical machine translation and the example based on machine translation approach.

2.5.2.1 Statistical Machine Translation Approach

The parameters of the statistical models used to create statistical machine translation (SMT) are gleaned from the analysis of bilingual text corpora. According to (Brown et al., 2018) Bayesian-based model for statistical machine translation (SMT), each given input in a SL can be transformed into any given sentence in the TL, and the translation that is given the highest probability by the system is the most appropriate. The concept that underpins SMT originates in information theory. Problems that can arise from SMT include alignment of sentences, statistical oddities, data degradation, idioms, and various word ordering (Beattie et al., 2022).

The challenges of Statistical Machine Translation Approach:

- The construction of a corpus can be expensive for users who have few resources available.
- Unanticipated outcomes have been produced. Fluency on the surface level can be misleading.
- Statistical machine translation is not very accurate when used on languages that have very varied syntax (e.g., Japanese and European languages).
- The advantages of European languages are given too much weight in this discussion.

2.5.2.2 Example-based Machine Translation Approach

Example-based machine translation, also known as EBMT, is defined by its reliance on a dual-language lexicon with parallel texts as its principal knowledge. The central concept of this type of translation is that it is accomplished by translating one thing into another using an analogy. There are four distinct phases to the EBMT process: example acquisition, example base management, example application, and example synthesis. The foundation of EBMT is the notion of translation by analogy. An example-based machine translation system can be trained using example translations, encoding the concept of translation by analogy (Xiao, R., & Hu, X. (2015).

EBMT systems are taught using multilingual parallel corpora, containing sentence pairs. These sentence pairings are used to train the example-based machine translation systems. The original sentences in one language are accompanied by their translations into another language in a sentence pair. This particular example demonstrates an illustration of a limited pair, which indicates that the phrases differ in only one aspect from one another (Ambati et al., 2012). The translations of sub sentential units are made much simpler to learn thanks to these sentences. Also, EBMT eliminates the requirement for manually created translation rules. However, EBMT suffers from a lack of computational efficiency, which is especially problematic for big databases, despite the fact that approaches for parallel computation can be utilized (Hutchins, 2005).

2.5.3 Hybrid Machine Translation Approach

By fusing statistical and rule-based translation approaches, a new method, the hybrid-based approach, has been established. This approach, which incorporates statistical and rule-based translating approaches, has been found to be more effective in the field of MT systems. This hybrid approach, which is based on both rules and data, is currently being used by a number of public and private MT sectors to advance translation from source to target language (Sindhu, et al., 2016).

There has been a recent dealing in interest for hybrid MT approaches that combine elements of different MT paradigms. Hybridization around the EBMT framework can be seen in the METIS-II MT system, which uses a multilingual glossary and a corpus of one language in the TL to forego the usual need for parallel corpora (Dirix et al., 2005). The hybrid approach has numerous potential uses. In certain cases, rule-based methods are used to perform initial translations, with statistical data then being used to amend or correct the translated text. On the flip side, rules are employed both before and after a statistical translation system does its calculations to refine the accuracy of its results. This new method of translation is superior to the old one since it offers more power, versatility, and command (Sindhu, et al., 2016).

This method of machine translation was developed by Google, and because no approach has been able to achieve an accuracy level that is considered to be sufficient, the development of hybrid systems for machine translation has become increasingly important. The accuracy of translations has significantly improved thanks to the efforts of a great number of hybrid machine translation systems the challenges in the Hybrid System include (Wu et al., 2016) The quality of the bilingual corpus has a direct influence on how accurate the translation will be. The process of creating a bilingual corpus that has a high level of similarity is very time-consuming and expensive. The challenges of Hybrid Machine Translation Approach:

- Creating a training corpus of high quality can be a challenging task.
- The hybrid machine translation algorithm is ineffective for language pairs that have few available resources.

2.5.4 Approaches to Machine Translation Evaluation

Although it is insurmountable to provide an exhaustive study of the literature on MT appraisal, it is essential to highlight some aspects and trends. Two distinctive traits were established throughout the history of assessment: fluency and fidelity. There is a widespread belief, particularly among MT researchers, that evaluation results are considered satisfactory if a model generates sentences that are well-formed syntactically and semantically, does not pervert the idea of the input, and does not produce overall poorly formed sentences (Dušek et al., 2020). The most popular additional evaluation factors used by system developers and real-world users are cost, system extensibility. In the realm of real-world applications, the importance of quality may be overridden by other factors according to Church and Hovy (1993). Various techniques have been proposed to gauge fluency in machine translation, some of which focus on specific grammatical structures, others rate the entire sentence on a scale. Others, determine fluency by assessing the translated text ambiguity in respect to an index generated from a collection of ideal translations (Papineni et al., 2001). The correlation between these methods is yet to be examined.

Fidelity in machine translation is typically assessed by experts who rate the extent to which the system's output accurately conveys the meaning of the source text or a human-generated translation. This is often done on a scale and determined by the percentage of meaning retained in the translation. Another approach that has been proposed but yet to be fully explored is to use a vector space of words to project both the system's output and human translations and then measure the degree of deviation from the average of the human translations (Thompson, 1992).

2.6 Textual Problems in Machine Translation

Gaspari, Almaghout, and Doherty (2015) conducted a study on machine translation proficiencies that used data from 438 validated respondents. The result opined that the incorporation of Machine Translation (MT) has resulted in significant changes in the human translation technique, with proofreading being applied only to high-quality content. Taivalkoski-Shilov (2019) investigated some of the most important ethical problems to address while using or modifying technology technologies for literary translation. The findings suggest that the use of CAT and interactive MT in literary translation will likely increase in the coming years.

Different languages have distinct characteristics, particularly grammatical rules and expressing patterns. Moreover, discrepancy in information expression in terms of linguistic information such as lexicon, sentence, sentence structures, and meaning exist in different language symbol systems, posing a barrier to machine translation. Chinese, as an example, is a parataxis language with a large number of structurally unfinished sentences, whereas English is a hypotaxis language and connection words play an essential role (Everaert et al., 2015). Machine translation of Chinese to English frequently lacks logical connectives, resulting in loose and incompact or logically unclear phrases. Errors such as poor word usage and unnecessary terms are common during the translation process into Chinese. In most cases, machine translation efforts necessitate translator post-editing (Maxom, 2010). However, since translators' resources are limited, people are faced with a severe dilemma. Manual translation has high quality and fees but low output and supply. machine translation has high output and low fees, but low quality (Bywood et al., 2017).

2.7 Semantic and Syntactic Problems of Machine Translation

Simply put, semantics is about meaning, whereas syntax is about grammar. Semantics is the process by which the lexicon, grammatical structure, tone, and other elements of a sentence work together to convey its meaning. Syntax is the set of rules that must be followed to ensure that a sentence is grammatically correct. The cornerstone of every translation is effective communication. The main objective of translation is to make material understandable and legible for the target audience, and the clarity of sentence can be impacted by grammar (Kreidler, 2002). Machine translation cannot solve the quality challenge of cross-lingual information conversion adequately. According to Cronin (2013), in the context of global communication, interlingual activities are essential and thus translation plays a crucial role in globalization. However, many individuals may lack the proficiency or willingness to overcome linguistic barriers, requiring the assistance of professional translators and interpreters to access information beyond their own linguistic capabilities. These professionals serve as interlingual and intercultural communicators, facilitating access to information and increasing cultural understanding. The study rarely detect translation because of its nature, even when it is right in front of our eyes (e.g., Kenny, 1996). Traditional human translation just cannot keep up with today's translation needs, given the proliferation of digital content and the emerging interactive online culture of Web 2.0 technologies (O'Reilly, 2005).

The variation in sentence structure between Chinese and English can present challenges for Machine Translation Systems (MTS) in accurately interpreting sentence components. Chinese often omits the subject while it is a necessary component in English. This can result in English statements without a subject during the machine translation process. Additionally, the complexity of language patterns poses difficulties for MTS, particularly in Chinese-English translation (Klubička, 2018). Chinese tends to use the active voice more frequently, whereas English commonly utilizes the passive voice, particularly in informal forms. MTS rely on the original text's grammatical structure, which can result in a high number of passive sentences in the translation, diminishing readability and potentially altering sentence expression (Wang et al., 2019).

2.8 Empirical Studies on MT Usage

Without a doubt, the use of MTS by students in educational institutions have had a transformative impact on their education and in their everyday lives. Students utilize MT to learn new words, translate, understand what they are reading, and do writing assignments (Alhaisoni & Alhasysony, 2017). These tools help students learn a language in three ways: cognitively, linguistically, and emotionally. It has been suggested that utilizing machine translation can have a positive impact on cognitive function by reducing mental effort required for language comprehension (Baraniello et al., 2016; Lewis, 1997) and by facilitating autonomous learning (Godwin-Jones, 2015; Wong & Lee, 2016). From a lexical point of view, MT helps with vocabulary and grammar improves reading comprehension and writing, and ultimately helps with language learning (Li, 2022) said that using MT can "force students to think about language as a tool for communication, not as a list of vocabulary words or phrases taken out of context." From an emotional point of view, it decreases language anxiety, boosts motivation and confidence, and makes the learning environment less scary. Studies also show that MT has problems, such as wrong sentences, wrong vocabulary, and wrong grammar (Bahri & Mahadi, 2016; Josefsson, 2011).

Multiple studies came to the conclusion that MT could be of assistance to students when they were revising their writing in their second language. According to Garcia and Pena (2011), MT posting enables learners to concentrate more on the writing process and proofreading. According to Kliffer (2005), MT posting allows learners use L2 knowledge that they already have and make corrections to their writing in the target language. In addition, Lee (2020) MT can be of assistance to students learning English as a foreign language who frequently struggle to get personal response about their writing while studying in a classroom setting. Students can receive individualized feedback, be provided with word-based and sentence-based choices, and thus be assisted in identifying and correcting errors as a result of using this tool. In addition, MT places a greater emphasis on lexico-grammatical errors and requires students to independently locate and correct their own errors, as well as solve problems and come to a conclusion (Lee, 2020). Students are able to develop skills related to writing in a second language that require self-directed and independent learning as a result of doing so (Bernardini, 2016; Garcia & Pena, 2011). This study, Al-Mansour, (2012) compares employing MT alongside the traditional way of translation to using the traditional approach alone. The researchers hypothesize that students who were taught using computer-assisted English language teaching in addition to the traditional way outperformed those who were taught using the traditional method alone. The results show that employing a computer in English language training to university students improves student achievement. This supports studies by Garcia and Pena (2011) which indicated that MT assisted learners in writing more effectively with less error.

From cognitive, linguistic, and affective perspectives, MT aids in student language learning. From a cognitive perspective, MT can ease cognitive effort by performing initial translations (Baraniello et al., 2016; Lewis, 1997) and can facilitate selfgoverned learning (Godwin-Jones, 2015; Wong & Lee, 2016). Linguistically, MT can support language learning by reinforcing semantic and syntactic intelligence (Bahri & Mahadi, 2016; Doherty & Kenny, 2014; Wong & Lee, 2016), enhancing writing and reading fluency (Alhaisoni & Alhaysony, 2017; Garcia & Pena, 2011; Kumar, 2012), and essentially fostering second language acquisition (Belam, 2003; Nino, 2009; Shei, 2002; Wong & Lee, 2016). MT can also encourage students to view language as a tool for communication, rather than just a collection of isolated terminologies (Williams 2006). Emotioally, MT can reduce language anxiety and improve creativity and boldness (Kliffer, 2008; Nino, 2008), and foster a safe learning environment (Nino, 2009).

Also, the usage of MT output texts in academic settings might raise ethical concerns due to the possibility of academic plagiarism; as a result, there have been extensive arguments regarding its role and application in recent years. The kind of assignment at hand has a significant role in determining whether or not the use of MT will result in instances of academic dishonesty and plagiarism from the point of view of the students. It is common knowledge that students should not utilize MT for tests or other work that will be graded (Peris, Domingo, & Casacuberta, F. 2017) and this is especially true when the assignments require them to do translation duties (Domingo et al., 2017). The length of the translation is also important. When the translation process was lengthy, a greater proportion of respondents considered the utilization of MT to be "immoral" or "totally unethical". Although instructors and students expressed comparable perspectives regarding the moral implications of MT use, teachers adhered to a more stringent benchmark (Balahur, 2014) The fairness seen by students in terms of how much they respect their own work as human translators is reflected in the ethical judgment of the employment of MT software. It is reasonable to hypothesize that their understanding of ethics is the determining factor in whether or not they make appropriate use of the MT technology, which in turn can have an impact on their development as professional translators.

2.9 MT Usability Amongst Students

Without a doubt, more and more students are using MT in their classes and in their everyday lives. Users utilize MT to learn new words, translate, understand what reading, and do writing assignments because they think it is a good supplement for language learning (Alhaisoni & Alhasysony, 2017). According to the research, MT helps students learn a language in three ways: cognitively, linguistically, and emotionally. From a cognitive point of view, it decreases the amount of work your brain has to do by doing preliminary translations (Baraniello et al., 2016; Lewis, 1997) and encourages self-directed learning (Godwin-Jones, 2015; Wong & Lee, 2016). From a linguistic point of view, MT helps with vocabulary and grammar improves reading comprehension and writing, and ultimately helps with language learning (Li, 2022) said that using MT can "force students to think about language as a tool for communication, not as a list of vocabulary words or phrases taken out of context." From an emotional point of view, it decreases language anxiety, boosts motivation and confidence, and makes the learning environment less scary. Studies also show that MT has problems, such as wrong sentences, wrong vocabulary, and wrong grammar (Bahri & Mahadi, 2016; Josefsson, 2011).

Although, there is a growing demand for MT in the context of education, the validity of MT has not yet been established to its full potential. Therefore, it is necessary for us to figure out how to make the most of MT, which is a flawed instrument, in order to achieve beneficial learning results in the language classroom (Zeroual, &

Lakhouaja, 2020). There hasn't been a lot of research done on this topic up until this point. As a result, it is essential to conduct research into the ways in which MT can improve students' language learning on the basis of actual evidence and to recognize both the possible benefits and the potential dangers of MT's use in educational settings. The majority of studies that look at MT as a technique for second language acquisition concentrate on MT of students' first language writing and postediting the translation that is given. As a consequence of this, the studies hold that MT is a poor model (Nio, 2004, 2009), as it is replete with lexico-grammatical faults that need to be fixed through postediting. In contrast, the study that is being presented here views MT in the context of CALL as a tool that can promote language learning by providing students with lexico-grammatical references in the target language. Because postediting does not allow for direct measurement of student improvement, this study employs a different task design, having students translate their L1 writing into L2 on their own without the assistance of MT, and then having them correct their L2 writing using the MT translation as a point of comparison. The objective of this study is to investigate the value of MT in terms of helping students improve their writing in their second language (Abadi et al., 2016).

Previous research has found a slew of educational advantages to using machine translation in language acquisition. As machine translation technology advances, it is projected to be used more frequently in academic settings, emphasizing the importance of investigating the usability of these systems. To the best knowledge of the researcher, the use of CAT tools among Eastern Mediterranean University students is yet to be extensively explored. As a result, we sought to use SUMI to collect data on the use of CAT tools by Eastern Mediterranean University students. The SUMI review considers the system's efficiency, affect, utility, control, and learnability.

2.10 The Element of Perceived Quality of MTs

The element of perceived quality in machine translations (MTs) refers to how well the translation is perceived by the end user. This can be influenced by factors such as fluency, usefulness, accuracy, control and learnability. Perceived quality is subjective and can vary depending on the user's language proficiency, expectations, and purpose for using the translation. It is important for MT providers to continually assess and improve the perceived quality of their translations to ensure they meet the needs and expectations of their users.

2.10.1 Usability of MT

ISO [ISO/IEC 25022] defines usability to be "the potential of a software product to be perceived, learnt, utilized, and that is attractive to the user when utilized in specified conditions." There are three main characteristics of good usability:

- First, effectiveness, the extent to which software aids user to accomplish goals.
- Second, efficiency, which is the degree to which the resources expended in accomplishing those goals are proportional to the degree to which users succeed in accomplishing those goals.
- Third, satisfaction, which is the degree to which users are at ease while using the software and have a favorable impression of it (Frøkjær et., al, 2000).

The use of technology has become crucial in translation. Computer-assisted translation (CAT) techniques are widely used by translators to increase productivity without sacrificing quality. The success of CAT tools can be attributed to their ability to provide a manageable setting in which to carry out translation. Little has been done to explore the practicality of these resources, especially among Turkish translators.

2.10.2 Efficiency of MT

When a translator uses a piece of software, they may experience varying degrees of efficiency, defined as either the belief that the tool helps users get their work done quickly, effectively, and economically or the belief that the software is hindering their work. For the purposes of this definition, "efficiency" connects between:

- The precision and thoroughness with which users accomplish their goals and
- The amount of effort required to accomplish those goals. In that case, developers' perceptions of software efficiency are strongly correlated with efforts to enhance the program's usability. This indicates that a user's level of familiarity with the software's inner workings directly affects its usability.

2.10.3 Affect of MT

Here, this term means the degree upon which translator's mental state is either positively or negatively affected by the translator's interactions with the tool. The metric measures how the software makes the user feel in general. User satisfaction and interest in software are indicators of high affect. The improvement of software usability is a direct result of its development and documentation. The clarity of its intended purpose and the ease with which it may be understood by the readers of user guides and other documentation both contribute to a higher rate of adoption.

2.10.4 Helpfulness

In this context, ‘helpfulness’ is tagged to translator's impression that the program provides constructive feedback and works to fix any technical issues. How effectively does the software explain itself and how well is it supported by tutorials and other resources. This tool combined with tutorial documentation; the help menu can significantly improve usability. The usability of software improves when it is equipped with a comprehensive help system and feature-specific documentation.

2.10.5 Control

It refers to how users feel about the predictability and reliability of the tools' reactions to their input and directions. To what extent the user feels in command of the software rather than at the tasks. The improvements in software have been correlated with an increase in the use of instructions to control operations. The use of commands to perform actions is essential for usability.

2.10.6 Learnability

The ease with which a translator is able to learn the software is referred to as its "learnability," and it is an indicator of how well the software's tutorial interface, manuals. This also includes having to relearn on how to operate the program after an extended period of inactivity. Learnability is tagged to how quickly and easily a user masters the tool. The better user experience can be achieved by following simple rules for usability. The rules should be drafted in a way that facilitates their implementation.

2.11 Conceptual Framework

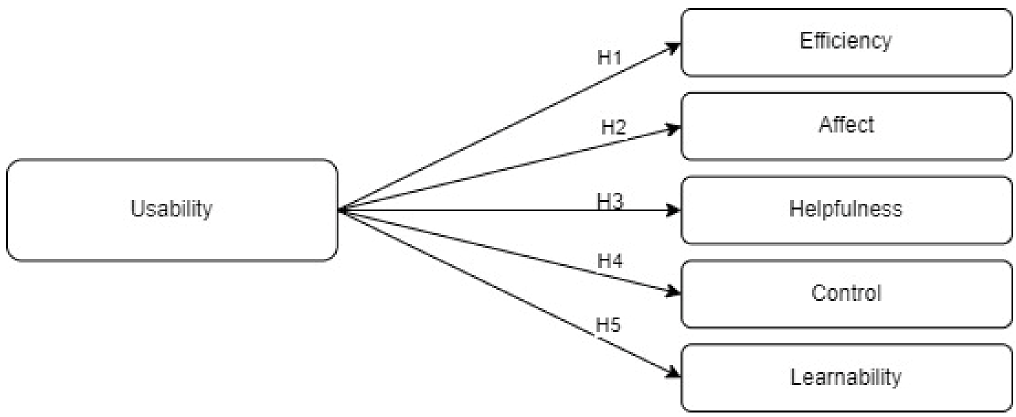

Figure 1.2: MT usability and its relationship with the variables.

From the conceptual framework, the study consists of 6 hypotheses.

2.12 Research Hypothesis

In this study, five hypotheses were formulated. The hypotheses include:

- H1: The developed model conveys and assists in solving the practical problems in a helpful way.
- H2: Users' will find the developed model efficient in carrying out translation tasks.
- H3: The user's emotional state during interaction with the product is influenced by the product's ability to evoke an emotional response.
- H4: The user's perception of model's responsiveness and consistency in responding to their inputs and commands is influenced by their sense of control over the software.
- H5: The ease to which users operate the model is influenced by its level of learnability.
- H6: The Hybrid machine translation approach, which combines both rule-based and statistical machine translation methods, will result in overall improved user experience.

2.13 SUMI for Measuring Usability

Usability is a critical aspect of product design and development, as it determines the effectiveness with which users are able to achieve their goals using a product. Kulkarni et al. (2020) evaluate the TEIM (The Evolved Integrated Model) of Software for Engineering & Human Computer Interaction called PS for usability, using SUMI. A study by Mansor et al. (2012) also used SUMI to assess a cost estimation tool they named WebCost, which was developed using Java programming language. The results of the SUMI analysis showed that users were satisfied with the software, and it was concluded that it was feasible to use.

Similarly, a study by Khairunisa et al. (2020) used SUMI to evaluate a student information academic system. The respondents were students of the multimedia engineering study program. The results of the SUMI assessment showed that the system was feasible to use and met the SUMI assessment standards. The results of the study were also in line with that of Darmawan et al. (2021) who also used SUMI as an evaluation tool to measure the usability of the mobile-based Smart Regency Information System. The method adopted in this study follows the Life Cycle of the Knowledge Management System (KMSLC). According to the Authors, the result of the study is expected to provide valuable insights into the factors that impact the success of knowledge management for smart regency services.

To the extent of our research however, SUMI has not been used as an evaluation tool for MT systems. However, we do believe that it would be very effective a tool for testing our developed model for usability from users' perspective.

2.14 Summary

The summary of this chapter comprises the history, development, and definition of MT. The chapter also provides different approaches to MT, such as rule-based MT, corpus-based MT, and hybrid, semantic, and textual approaches to MT and MTSs. This study is based on empirical studies of MT among students. The other part of this chapter presents an in-depth overview of prior empirical and theoretical literature on MT usability as well as the influence of MT usability on the perceived quality of MT adoption. The conceptual framework of the study and the research hypotheses were developed and discussed extensively.

Chapter 3

METHODOLOGY

The study design, sample size, target population, research instrument, and statistical analysis are some of the issues discussed in this chapter.

3.1 Data Collection Strategies

In order to explore the usage, challenges, and reliability of using MTS by students in Eastern Mediterranean University, the English and Turkish version of the Software Usability Measurement Inventory (SUMI) was used to appraise MTS tools. SUMI is a tried-and-true method of evaluating software quality from the end user's perspective. It is a highly acknowledged means to evaluate software usage on a global scale. It is a 50-item survey that evaluates five distinct factors: efficiency, affect, helpfulness, control, and learnability (Kirakowski, 1986). Kirakowski first created the questionnaire in 1986, and it has since been utilized in a number of usability tests. ISO/IEC 9126, an international standard designed to guarantee the quality of all software-intensive products, including systems that are safety-critical where software failure can result in loss of life, has also recognized the assessment tool as a valid measurement for evaluating end-user experience. A global usability scale is also included in the survey, which measures the translator's overall happiness with the tool. Participants choose one of three options ("agree," "undecided," or "disagree") to weigh their sentiments toward MTS tools.

3.2 Data Collection

The first step in addressing the research topic, verifying the hypotheses, and assessing the findings is the collection of data from all reliable sources. There are two types of data collection strategies: secondary and primary. The primary source of data for this study was an online survey that collected primary data. A data source is specifically used to gather "primary data." It is frequently acquired specifically for a study project and may be made publicly available for use in future research.

3.3 Population of the Study

To achieve accurate results in the SUMI evaluation, a minimum sample size of 10-12 participants is required (Kirakowski, 1986). However, a sample of 19 respondents is needed to complete the survey in this study. Participants would be chosen on the premise of representing diverse groups within the EMU community and coming from various international backgrounds in order for the data to be representative.

3.4 Validity

SUMI has been the subject of three different types of validity investigations. To begin, the MUSiC consortium's industrial partners employed SUMI as a component of the MUSiC usability evaluation toolset (Kelly, 1994). Second, the Human Factors Research Group has completed a variety of laboratory-based research, as well as studies for industrial clients on a consulting basis. Laboratory studies have limited ecological validity; consultancy studies are almost typically commissioned under stringent confidentiality agreements and are not publicly disclosed except in broad strokes. In addition to empirical validation, the SUMI subscales have been compared to the ISO 9241 part 10 discourse principles for some theory-based validation (Prumper, 1993).

3.5 Data Analysis Strategy

When the survey is finished, the replies would be scored and compared to a standards database called SUMISCO, a specific application included in the SUMI assessment package. When evaluating software usability, the standardization database serves as a benchmark. A result of 40-60 is regarded acceptable, while a score of less than 40 is deemed unsatisfactory. SUMI Survey, SUMI is a globally recognized benchmark for assessing software's usability. It is a 50-item questionnaire designed to assess five distinct characteristics: efficiency, affect, helpfulness, control, and learnability. The SUMI website can be accessed at http://sumi.uxp.ie/.

3.6 Ethical Approach

The survey was conducted with the highest regard for ethical considerations. Participants were fully informed about the purpose and nature of the survey, and their consent was obtained prior to their participation. Confidentiality and anonymity were maintained throughout the process, and all data collected was securely stored. The rights of the participants were respected, and no form of harm or coercion was inflicted upon them. The ethical guidelines of the relevant professional bodies were strictly adhered to, ensuring that the results of the survey accurately reflect the views and experiences of the participants. The participants were also informed that their responses and data would be handled anonymously and that the information acquired would only be used to advance scientific research.

Chapter 4

SYSTEM DEVELOPMENT AND HYPOTHESIS

The chapter will provide information about the created system, including its overview, development method, design, architecture, database design, and other features. The system is built on earlier work by Labaka, et al, 2014 and uses parallel corpora from Argos Open tech for model training.

4.1 System Summary

Due to the advantages and disadvantages of MT approaches, HMT models have emerged in the recent literature with the aim of combining the advantages of both approaches. This section introduces a hybrid design that leverages the benefits of RBMT and SMT. The hybridisation is achieved using an open-source translation library system from Argos open tech to drive the main translation process. Our hybrid system will be referred to as "Xell".

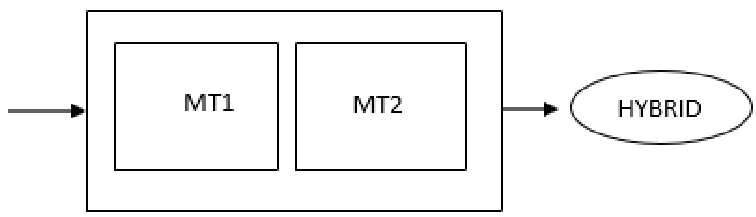

Figure 4.1:2 Architecture of the Hybrid Approach

The integration of SMT and RBMT is driven by the premise that RBMT is capable of executing parsing, rule-based transfer, and reordering processes to generate a coherent output structure, while SMT provides support for lexical selection through the provision of multiple translation alternatives for the source language components (Labaka, et al., 2014). Practically, the SMT component can also serve as a back-up. The hybrid decoder can still use translations generated by the SMT system alone, even for long segments or complete source sentences, if the RBMT unit makes a significant error in analysing, transfer or re-ordering. The decoder also takes fluency into account by using language models. Fig. 4.2 shows an outline of the hybrid system and its main units.

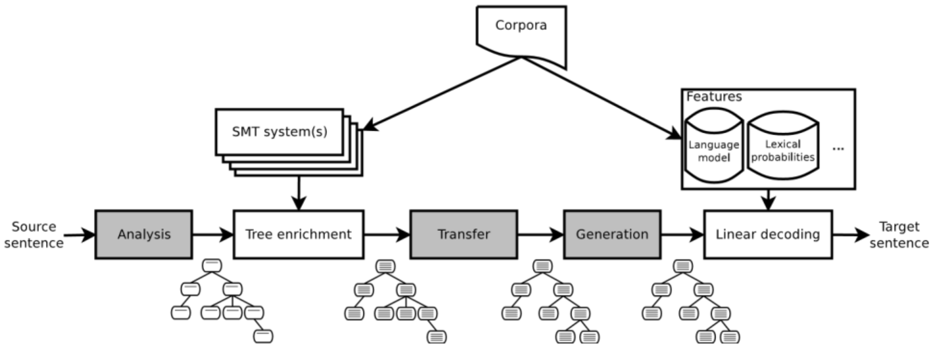

Figure 4.2: Architecture of the hybrid MT system (Labaka, et al., 2014).

4.2 Hybrid Architecture

The design of Xell takes into account the strengths and limitations of traditional RBMT and SMT systems. Drawing from the model proposed by Labaka, et al. (2014), the hybrid system has three main goals. Firstly, it should allow the RBMT system to handle the vast majority of the syntactical pattern and order in the translation process. Secondly, it should be able to correct any errors in the syntactic analysis by relying on SMT-based translations. Thirdly, the hybrid system should consider the SMT's localized translations of short segments, as they can enhance lexical selection. In addition to these three key aspects, the hybrid system also incorporates a statistics language framework that can help produce more fluent results.

Labaka et al. (2014) introduced a hybrid system known as Matxin that combines the benefits of RBMT and SMT to enhance the translation tree generated by RBMT. Xell, which follows the architectural and data structure principles of Matxin, further develops this approach by incorporating two novel steps into the transfer model originally utilized by Matxin.

An additional enhancement phase is added after the analysis phase and before the transfer. During this phase, SMT translation candidates are assigned to each node of the parse tree, covering the text segments dominated by the node, which can range from single lexical markers to the entire SL represented at the base of the tree.

Subsequently, a monotonic decoding step is employed to choose the definitive translation from among the partial RBMT and SMT translation candidates in the enhanced tree. The integration of the Xell modules into the RBMT pipeline is depicted in Figure 4.2.

4.3 Corpus and Training Data

To train a highly effective translation model, a large and diverse parallel corpus is crucial. This requires finding many sentence pairs that have been translated into different languages and are otherwise identical. The size and variety of the training data is the main differentiator between a poor translation system and a top-performing one like Google Translate. Fortunate for us, there are numerous sources for obtaining parallel data. For formal and legal language, organizations like the European Union and the United Nations provide translated documents. For more conversational language, we can find parallel data from movies and TV shows that come with machine-readable subtitles in multiple languages. This also applies to more recent content with subtitles like Blu-rays and YouTube videos.

While finding the required parallel data might be easy, collecting and cleaning this data is a time-consuming task, the team at Argos Open Tech has already done the work of gathering and preparing sentence pairs in many languages. With their help, we can easily access almost 85 million translated sentence pairs in about 12 different languages including Turkish, ready for use in developing our translation model.

4.4 Software and Hardware Requirements

To build the code that connects and processes the text, we used the programming language Python 3.1 on a computer running the Windows 10 operating system. A standard personal computer with enough power is sufficient, but a graphics card with at least 8GB of video memory is necessary. We also need to Install Microsoft Visual C++ Build Tools.

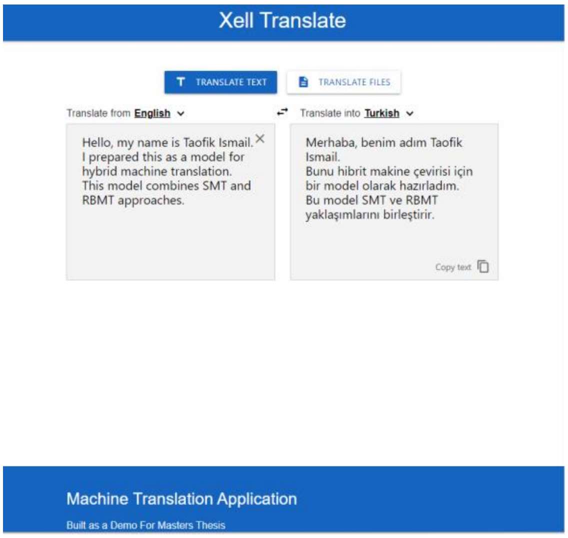

Figure 4.3: Xell Translate User Interface.

Chapter 5

DATA ANALYSIS

5.1 Sumi Setup

Before administering the SUMI questionnaire, consent was obtained from participants who then completed it online to produce a comprehensive report. The SUMI results were analyzed by evaluating scores to determine the software's usability. These scores were reported as a total score and scores for each usability aspect, which could be compared to standard norms or benchmark scores Identifying the capabilities and limitations of the system.

The SUMI questionnaire consists of 50 questions evaluating the participant's perspective and experience with the system. Participants were offered three choices for their responses: "agree", "undecided", or "disagree". After the questionnaires were filled out, the SUMISCO software, part of the SUMI evaluation suite, calculated the scores and compared them to a standardized database. The average score in the standardized database is 50, with a standard deviation of 10. Systems scoring between 40-60 on the SUMI evaluation are considered to have typical usability compared to the majority of commercially successful products in the standardized database (scores both above and below this range are included). A higher score indicates a better level of usability, while a lower score suggests areas for improvement.

5.2 Aspects of Model Usability

The usability test followed user interaction with the model and was performed using the SUMI questionnaire, the only internationally standardized and validated commercial tool for measuring software usability from the user's perspective. The SUMI evaluation is a reliable means for evaluating software quality from the user's point of view, with an integrated analysis and reporting tool backed by a comprehensive reference database. The resulting report is split into a global scale and five SUMI-defined sub-scales, in line with research indicating that user experience can be divided into five areas (Kirakowski, 1986):

- Efficiency: This is the user's impression that the software is able to perform the task or tasks in a fast, accurate and economical fashion or, in the reverse case, that the software is a hindrance to the users' performance.
- Affect: This is a technical term used in psychology to describe emotional feelings. In this instance, it refers to the user feeling mentally engaged and comfortable, or the reverse, as an outcome of interaction with the product.
- Helpfulness: This describes the user's sense that the system conveys and assists in solving the practical problems in a helpful way.
- Control: This subscale refers to the user's perception that the software responds to input and commands in a normal and consistent manner.
- Learnability: The level to which the users' find the software relatively easy to learn and operate.

5.3 Results for the Developed Model

The results of the usability evaluation of the proposed prototype are outlined in this section. To assess the system's usability, a thorough usability test survey was conducted. Participants, who were students at EMU, were asked to interact with the developed model using the provided scenarios. 19 students partook in the online survey, exceeding the minimum recommended by SUMI of 12 participants. Out of these 19 participants, 17 responses were considered valid and could be analyzed, while the remaining two were deemed invalid.

The table 5.1 presents the user data for the Global and individual SUMI scale scores, arranged in ascending order based on their Global scores, with the highest scores appearing at the top of the table. The typical highest scores for individual subscales range around 72, and the lowest scores around 19.

Table 5.1: User data sets for subscales

Participant	Global	Efficiency	Affect	Helpfulness	Control	Learnability
1	75	67	54	72	61	61
2	68	67	62	65	63	60
3	67	64	69	62	66	55
4	62	61	48	62	54	67
5	62	64	63	59	70	69
6	61	67	55	61	53	67
7	60	64	64	52	58	67
8	60	63	54	55	61	54
9	56	61	59	47	56	55
10	54	41	63	51	51	53
11	53	51	49	50	49	58
12	51	57	42	52	64	48
13	49	49	36	58	42	46
14	49	62	63	48	41	59
15	44	53	53	41	50	46
16	44	53	36	42	47	47
17	44	47	49	40	48	49

The SUMI scores are transformed using a z-score, resulting in an average mean of 50 with a standard deviation of 10. This indicates that scores above 50 indicate higher than average user satisfaction. As demonstrated in Table 5.2, the developed model achieved a global score of 56.41, which is within the expected range and shows that user satisfaction with the tool is above average, thereby validating H6 which says that the developed model which combines both rule-based and statistical machine translation methods, will result in overall improved user experience. The table also displays the descriptive statistics including mean, median, standard deviation, interquartile range (IQR), minimum, and maximum scores for each individual as well as the overall scale. A statistical analysis of the data reveals that the Efficiency sub-scale obtained the highest score of 58.29, implying a relative efficacy of the developed model in executing assigned tasks, thus validating H2. All other sub-scales obtained mean scores that exceeded 50, which indicates an overall user satisfaction across the various aspects of the evaluation, and validating H3, H4 and H5. The median, as calculated from the data arranged in numerical order, is represented by the median boxplot in Figure 5.2.

Table 5.2: SUMI result summary

	Mean	S. D	Median	IQR	Minimum	Maximum
Global	56.41	9.08	56.0	13.0	44	75
Efficiency	58.29	7.90	61.0	12.0	41	67
Affect	54.06	9.80	54.0	14.5	36	69
Helpfulness	53.94	8.98	52.0	14.0	40	72
Controllability	54.94	8.41	54.0	13.5	41	70
Learnability	56.53	7.87	55.0	15.5	46	69

Figure 5.1 Gives a graphical representation of the means and standard deviations for individual subscales. The mean, which is the central value of a set of numbers, and the standard deviation, which measures the dispersion of these numbers around the mean, are depicted. The figure showcases the average and deviation statistics for the SUMI and Global Usability scales in the studied sample. The mark in the circle represents the mean, while the bars extending from it indicate one standard deviation in either

direction from the mean. It can be observed that the mean scores for all sub-scales are above average and fall within the desired range of 40 to 60, indicating overall user satisfaction with regards to usability and suggesting that the model effectively meets its main functional requirements thereby validating H6.

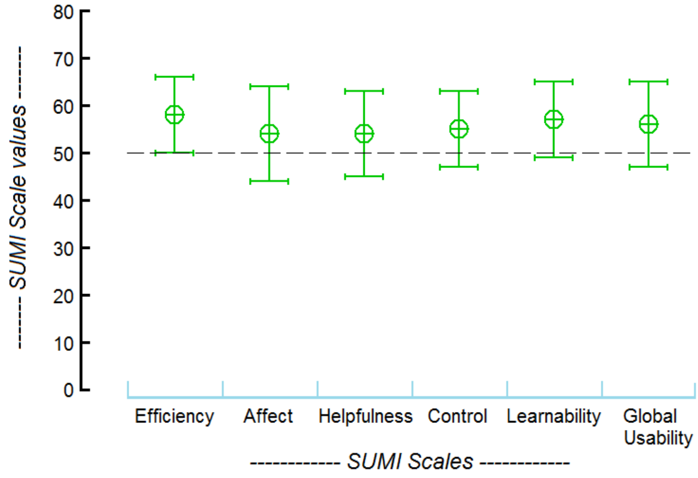

Figure 5.1: SUMI scale profile; means with standard deviation.

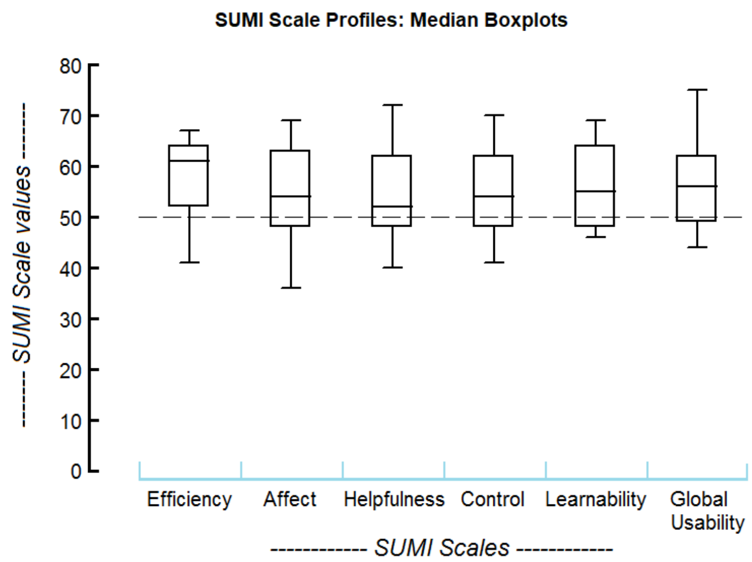

Figure 5.2: SUMI scale profile; median boxplot

The median is basically the middle value of a set of numbers. It is the numerical value separating the lower half of the sample from the upper half, such that 50% of the observations fall below and 50% fall above it. The quartiles, particularly the first quartile (25th percentile) and the third quartile (75th percentile), provide additional information about the spread of the sample around the median. These values are visualized on a box plot (refer to Figure 5.2), where the median is represented by a horizontal line through the box and the quartiles are defined by the edges of the box. The interquartile range (IQR) is the range between the first and third quartiles, while the whiskers on either end of the box in figure 5.2 indicate the extent of the data where 95% of the data in the sample is predicted to fall.

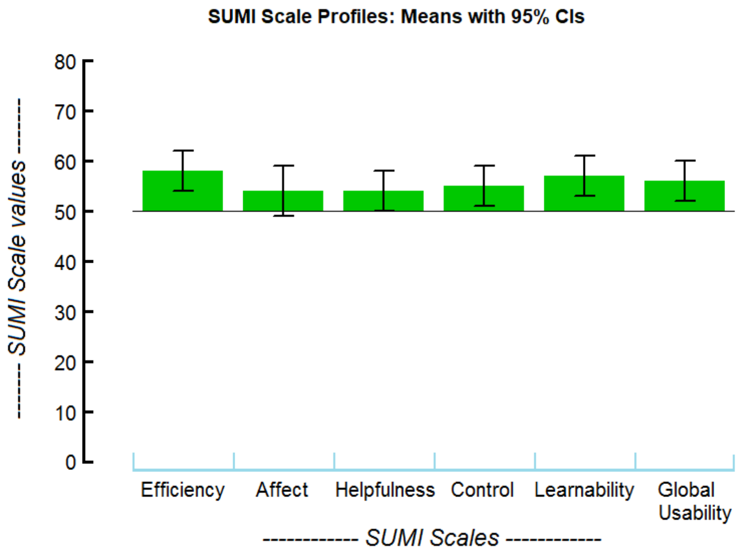

Figure 5.3: Means with 95% CI’s

Figure 5.3 presents a bar graph that summarizes the mean scores obtained on different subscales of the SUMI evaluation. The height of each bar represents the average score for a specific subscale. When the average score exceeds 50 (which is the benchmark), the bar is depicted in green. Conversely, if the average score falls below 50, the bar is shown in red (our bars are all green as our scores are all above 50 as seen in Table 5.2).

The graph in question also displays the range of scores within which we can have a high degree of confidence (95%) that the true average score would reside, if the same survey were conducted an infinite number of times using the same sample of participants. This is represented by the vertical "staples" on the graph. The presence of the 50 mark within or outside of this range has implications for our conclusions regarding the significance of the SUMI score for that particular aspect. If the 50 mark lies outside of the confidence interval, it suggests that the SUMI score for that aspect is significantly different from the reference standard. On the other hand, if the 50 mark is situated within the confidence interval, more caution is necessary in drawing conclusions, as it implies that the difference from the reference standard may not be statistically significant.

Chapter 6

DISCUSSION AND CONCLUSION

6.1 Conclusion

Machine translation has been around for over 50 years. Many methods and technologies have been tried, but they still have some shortcomings. HMT, which combines multiple technologies, was created to fix these problems and improve translation quality. This study talks about different combinations of translation methods, the architecture of HMT system, and their benefits and drawbacks.

The study analyzed a group of computer-savvy students at Eastern Mediterranean University (EMU) who have previously used machine translation systems. The six hypotheses proposed for the study were supported by the findings, indicating that in an appropriate setting, the model can improve language learning by providing students with linguistic and grammatical references in the target language. The study, as per ISO/IEC 25022, concluded that well-functioning MTS have the capacity to translate text from one language to another via a computer system with the desired attributes. These conclusions are consistent with prior research on MTS (Zeroual & Lakhouaja, 2020; Deng & Yu, 2022).

An overview of the aims, objectives and contributions of the study was provided in the first part of the study. The literature review covered the historic progression of MT, competence, machine translation approaches and empirical studies on MT usability and the hypotheses of the study which were developed from the SUMI items. The study demonstrated the validity of its hypotheses through confirming a positive and significant correlation between machine translation (MT) usability and the factors that impact its perceived qualities. The results indicated that the developed hybrid MT model is of global standards in terms of usability as it enhances control, efficiency, affect, and helpfulness.

H1 aimed to examine the connection between the usability of machine translation (MT) and its helpfulness in addressing real-world issues. The results supported the hypothesis, with users reporting that the program provided valuable feedback and successfully addressed technical problems. This aligns with earlier studies by Garcia and Pena (2011), which found that MT support improves students' writing skills and reduces mistakes. H2 explored the perceived efficiency of the model from users' perspective. A statistical analysis of the data reveals that the Efficiency sub-scale obtained the highest score of 58.29, implying a relative efficacy of the developed model in executing assigned tasks.

H3 of the study aimed to explore perceived affect of the developed model from the Users' perspective. Results show that the model scored 54.06 exceeding the average benchmark of 50 serving as indicators of high affect. Furthermore, H4 explored the user's perception of model's responsiveness and consistency in responding to their inputs and commands is influenced by their sense of control over the software. SUMI results for controllability of the model returned a score of 54.94 indicating an above average level of perceived user control over the model. This is in line with findings by Amershi et al. (2019) stating that there is a need for improvements in software usability through the provision of clear instructions, control operations, and use of commands to perform actions.

H5 explored the learnability of the tool from users' perspective. The hypothesis was that the user-friendliness and ease of use of the model would positively impact its learnability. Previous research by Makhni et al. (2017) supports this idea, as they found that technology with user-friendly interfaces, necessary mechanisms, and integration functionality can have high levels of both usability and learnability. Improving the usability and learnability of MT tools was also found to enhance translators' overall experience and satisfaction (Alotaibi, 2020).

In conclusion, the study tested the developed hybrid MT model for usability from users' perspective using SUMI. Having scored a global usability mark of 56.41, the results of the study confirm that user satisfaction with the tool is above average, indicating overall user satisfaction with regards to usability and suggesting that the model effectively meets its main functional requirements thereby validating H6.

6.2 Recommendations for Future Research

The data was obtained from students at Eastern Mediterranean University in Famagusta, Northern Cyprus, through the administration of an online questionnaire utilizing a purposive sampling technique. Although certain limitations were encountered, such as the restricted scope of data collection to Famagusta, the study provides valuable insights for both academic and practical considerations, including theoretical implications and recommendations for future research.

Based on the results of the study, the following are proposed as recommendations for future endeavors:

- The scope of data collection in future studies should encompass a wider geographical range within Northern Cyprus to gain a comprehensive understanding of MT usage across different regions.
- Further investigations should consider approaching hybridalisation from other MT methodologies especially Neural approach.

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APPENDICIES

Appendix A: Questionnaire for the Study

The questionnaire used for this study can be accessed at http://sumi.uxp.ie

Appendix B: Application to use SUMI

Doğu Akdeniz Üniversitesi
"Erdem, Bilgi, Gelişim"

Eastern Mediterranean University
1 7rtåle' 'Knowledge, Advancement'

Socrates Sk. / Str., 99628, Gazimağusa, KUZEY KIBRIS / Famagusta, North Cyprus, via Mersin-10 TURKEY
Tel: (+90) 392 630 1245
Faks/Fax: (+90) 392 365
1574 http://sct.emu.edu.tr

Bilgisayar ve Teknoloji Yüksekokulu / School of Computing and Technology

Taofik Ayodele Ismail is a student at the school of computing and technolou, Eastern Mediterranean university and Iguarantee that his usage ofSUMI is solelyfor research purposes, andforms part ofhis research leading to a MSc in Information Technology. I guarantee that the student is not working in a consultancy relationship with any commercial interest as far as their use ofSUMI is concerned, and that I will help the student to take reasonable steps to protect the intellectualproperty rights and copyright ofSUMI.

Mustafa Tanel Babagil Asst. Prof. Dr. in School of Computing and Technoloo,' (I. T)

....

Appendix C: Permission to use SUMI

Gmail

Ayodele <taofikayodele@gmail.com>

SUMI record report

1 message

sumi_admin@uxp.ie <sumi_admin@uxp.ie> Sun, Nov 6, 2022 at 3:23 PM

To: Taofikayodele@gmail.com

Please find information about your SUMI setup.

Do not reply to this email.

Password:
Client: Taofik Ayodele Ismail
E-mail: Taofikayodele@gmail.com
Originating page: sumi.uxp.ie/en/
Creation date: 2022-11-06:13:20:32
Software evaluated: Xell Translate

Ask respondents to go to the originating page, and put in the password as given at the top, so that their responses will be validated. Passwords are NOT case sensitive.

When you have sufficient data, please contact jzk@uxp.ie to generate the professional report.

If you want to test the setup, please use 999 as a password and put your name in one of the plaintext fields.

If you need to know at any time how much data you have gathered, contact jzk@uxp.ie for a progress report.

Best wishes for your study.

Appendix D: Approval from Ethics Committee

Doğu Akdeniz Üniversitesi
"Erdem, Bilgi, Gelişim"

Eastern Mediterranean University
"Virtue, Knowledge, Advancement"

Galileo Galilei Sk. / Str.,
99628, Gazimağusa, KUZEY KIBRIS /
Famagusta, NORTH CYPRUS,
via Mersin 10, TURKEY
Tel: (+90) 392 630 1327
bayek@emu.edu.tr

Bilimsel Araştırma ve Yayın Etiği Kurulu (BAYEK) / Board of Scientific Research and Publication Ethics

Reference No: ETK00-2023-0024

26.01.2023

Subject: Your application for ethical approval.

Re: Taofik Ayodele Ismail and Asst. Prof. Dr. Mustafa Babagil

School of Computing and Technology.

EMU's Scientific Research and Publication Ethics Board (BAYEK) has approved the decision of the Ethics Board of School of Computing and Technology (date: 16.12.2022, issue: 22/1) granting Taofik Ayodele Ismail and Asst. Prof. Dr. Mustafa Babagil from the School of Computing and Technology to pursue their work titled **"Machine Translation: A Study on Turkish-English Translation Assisted by Software".**

Best Regards

Prof. Dr. Yücel Vural

Chair, Board of Scientific Research and Publication Ethics - EMU

YV/ek.

www.emu.edu.tr

Appendix E: Consent Form for Participants

Taofik Ayodele Ismail
MSc information Technology
05338730945
21506439@emu.edu.tr

CONSENT FORM

Dear Participant,

I am an MSc student conducting my thesis on the "MACHINE TRANSLATION: A STUDY ON TURKISH-ENGLISH TRANSLATION ASSISTED BY SOFTWARE ".

Please answer all the questions sincerely and be informed that your personal information and individual responses will be kept confidential and used only for research purposes. Collected Data can be used for future publications. For more information, please feel free to contact me or my MSc thesis supervisor.

Participating in this study is on the voluntary bases and you are free to withdraw from the study at any time. If you agree to participate, please fill the blanks below and provide your email address.

I have been properly informed of the objectives of this study and I agree to take part in it.

Email address:…………………………………………………….. Date: …………………

Taofik Ayodele Ismail
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Asst.Prof.Dr. Mustafa Babagil
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Easter Mediterranean University (EMU)
0392-630-2885
mustafa.babagil@emu.edu.tr

Appendix F: Turnitin Originality Result

Thesis

ORIGINALITY REPORT

14%	11%	8%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	etd.aau.edu.et Internet Source	2%
2	www.tandfonline.com Internet Source	1%
3	Zhu Aihua. "Man-Machine Translation—Future of Computer-Assisted Translation", Journal of Physics: Conference Series, 2021 Publication	1%
4	www.researchgate.net Internet Source	1%
5	mdpi-res.com Internet Source	<1%
6	Submitted to University of Wales, Bangor Student Paper	<1%
7	core.ac.uk Internet Source	<1%
8	Submitted to Eastern Illinois University Student Paper	<1%

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