

Investigating the Effectiveness of Neural Approach in Computer Assisted Translation (CAT) Systems

Awwal Olawole Ajide

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Prof. Dr. Ali Hakan Ulusoy
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Technology in Information Technology.

Asst. Prof. Dr. Ece Çelik
Director, School of Computing and
Technology

We certify that we have read this thesis and that in our opinion it is fully adequate in scope and quality as a thesis for the degree of Master of Technology in Information Technology.

Asst. Prof. Dr. Mustafa Tanel Babagil
Supervisor

Examining Committee

1. Assoc. Prof. Dr. Damla Karagözlü

2. Asst. Prof. Dr. Mustafa Tanel Babagil

3. Asst. Prof. Dr. Hüsnü Bayramoğlu

ABSTRACT

The usefulness of neural techniques in computer-assisted translation (CAT) is thoroughly examined. The development of neural networks has significantly improved machine translation and other aspects of natural language processing (NLP). By using computer aid, CAT is an NLP task that seeks to increase the effectiveness and caliber of human translation. However, because standard statistical-based approaches lack semantic comprehension, CAT's usefulness has been constrained. With their capacity to recognize intricate linguistic structures, neural networks have demonstrated significant promise in overcoming this restriction.

Comparison research between neural and conventional statistical-based methods was done to ascertain the effectiveness of neural approaches in CAT. Two datasets were employed in the investigation, one with technical and scientific documents and the other with legal words. The outcomes demonstrated that in terms of accuracy, fluency, and overall translation quality, neural-based models beat the conventional statistical-based methods. The neural models were very good at translating colloquial language and handling complicated sentence patterns.

The study also examined how many variables, including corpus size, language pairs, and training methods, affected the effectiveness of neural-based models. The results showed that the performance of neural-based models can be greatly enhanced by using larger corpus sizes and properly chosen training approaches. The results of this work show the potential of neural approaches in enhancing computer-assisted translation

efficacy and emphasize the significance of taking numerous elements into account when creating and training neural-based CAT systems.

Keywords: neural machine translation, computer-assisted translation, CAT system, out-of-vocabulary words, rare words, translation effectiveness, machine learning, natural language processing, deep learning, neural networks, language modeling.

ÖZ

Bilgisayar destekli çeviride (CAT) nöral tekniklerin kullanışlılığı bu bölümde kapsamlı bir şekilde incelenmektedir. Sinir ağlarının gelişimi, makine çevirisini ve doğal dil işlemenin (NLP) diğer yönlerini önemli ölçüde iyileştirmiştir. CAT, bilgisayar yardımı kullanarak insan çevirisinin etkinliğini ve kalitesini artırmayı amaçlayan bir NLP görevidir. Bununla birlikte, standart istatistiksel tabanlı yaklaşımlar semantik kavrayışa sahip olmadığından, CAT'in kullanışlılığı kısıtlanmıştır. Karmaşık dil yapılarını tanıma kapasiteleri ile sinir ağları, bu kısıtlamanın üstesinden gelmede önemli bir umut vaat ediyor.

CAT'ta nöral yaklaşımların etkinliğini belirlemek için nöral ve geleneksel istatistiksel tabanlı yöntemler arasında bir karşılaştırma araştırması yapıldı. Soruşturmada biri teknik ve bilimsel belgeler, diğeri hukuki sözcükler içeren iki veri seti kullanıldı. Sonuçlar, doğruluk, akıcılık ve genel çeviri kalitesi açısından nöral tabanlı modellerin geleneksel istatistiksel tabanlı yöntemleri yendiğini gösterdi. Nöral modeller günlük konuşma dilini çevirmede ve karmaşık cümle kalıplarını işlemede çok iyiydi.

Çalışma ayrıca, korpus boyutu, dil çiftleri ve eğitim yöntemleri dahil olmak üzere kaç değişkenin nöral tabanlı modellerin etkinliğini etkilediğini inceledi. Sonuçlar, nöral tabanlı modellerin performansının, daha büyük korpus boyutları ve uygun şekilde seçilmiş eğitim yaklaşımları kullanılarak büyük ölçüde artırılabilirliğini gösterdi. Bu çalışmanın sonuçları, bilgisayar destekli çeviri etkinliğini artırmada nöral yaklaşımların potansiyelini gösteriyor ve nöral tabanlı CAT sistemleri oluştururken ve eğitirken çok sayıda unsuru dikkate almanın önemini vurguluyor.

Anahtar Kelimeler: sinirsel makine çevirisi, bilgisayar destekli çeviri, CAT sistemi, kelime dağarcığı dışındaki sözcükler, nadir sözcükler, çeviri etkinliği, makine öğrenimi, doğal dil işleme, derin öğrenme, sinir ağları, dil modelleme.

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LIST OF ABBREVIATIONS

AMT	Adaptive Machine Translation
BERT	Bidirectional Encoder Representations for Transformers
BLEU	Bilingual Evaluation Understudy
BPE	Byte Pair Encoding
CAT	Computer Assisted Translation
EMU	Eastern Mediterranean University
GPU	Graphics Processing Units
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
METEOR	Metric for Translation with Explicit Ordering
MQM	Multidimensional Quality metrics
NFMT	Neural Fuzzy Machine Translation
NMT	Neural Machine Translation
OOV	Out of Vocabulary
RNN	Recurrent Neural Networks
Seq2Seq	Sequence to Sequence
SMT	Statistical Machine Translation
SUMI	Software Useability Measurement Inventory
TER	Translation Edit Rate
TM	Translation Memory
TPU	Tensor Processing units

Chapter 1

INTRODUCTION

The translation of text process has always been a complex and challenging procedure that calls for a high level of talent and knowledge (Searle, 1969). To help human translators with this effort, several methods and instruments have been developed throughout the years, including the usage of CAT systems. Due to their capacity to increase translations effectiveness and standardization by offering ideas and automatic support to translators throughout the process of translation, CAT systems have gained favor in recent years (Hutchins & Somers, 1992). CAT systems are designed to increase the effectiveness and accuracy of the translation process by offering automated support and ideas to translators throughout the translation process. They do this by studying the original text and using a variety of methods, like rule-based or statistical approaches, to produce translation suggestions the translator can take into account. The accuracy and effectiveness of the CAT system can still be improved, despite the drawbacks of these methodologies (Macklovitch, 2005).

Recent developments in Neural Machine Translation (NMT) models, in particular, have demonstrated amazing performance in transcribing text from a particular language to a different one (Sutskever et al., 2014). In accordance with research (Luong et al., 2015), traditional rule-based and statistical approaches do better than neural approaches at translating sentences fluently and naturally. However, because there hasn't been much study on the use of neural techniques in CAT systems, it's not

apparent if they may also be useful in this situation for enhancing translating quality and productivity (Liu & Li, 2020). The use of neural techniques in CAT systems has a lot of potential advantages. For instance, they are capable of handling complicated sentence patterns and common phrases and may be trained on enormous volumes of data (Koehn, 2017). They may additionally take context into account, which is crucial because certain words might have different meanings based on the situation (Mikolov et al., 2013). Additionally, neural techniques can be trained to generate interpretations that appear more genuine and flow more naturally, thereby rendering them simpler to read and understand (Bahdanau et al., 2015).

1.1 Statement of Research Problem

A technology-driven approach called computer assisted translation (CAT) helps human translators create translations that are more precise and productive. CAT systems have a variety of drawbacks notwithstanding their possible advantages, such as the need for standard terminologies, good syntax and grammar, and accurate contextualization. Traditional CAT systems have depended on rule-based and statistical techniques, resulting in drawbacks regarding translation quality and fluency (Koehn et al. 2010). The quality of translations has recently improved thanks to developments in neural machine translation (MT). Nevertheless, the use of neural approaches in CAT systems remains in its early stages, and more research is needed to fully understand both their possible benefits and limitations. Using technology to assist human translators while they translate is known as computer aided translation (CAT) (Bowker & Pearson, 2002). CAT has its roots in the 1950s, as researchers initially considered utilizing computers to speed up language translation. The initially developed CAT tools did not become widely accessible till the early 1980s (Hutchins & Somers, 1992). A challenge for CAT was the beginning of the storage and

computing limits of computers. Large-scale text processing and the storage of translation memory for later use were made challenging by this. Accurately transcribing grammatical idioms, complicated linguistic structures, and terminology peculiar to a given field were additional challenges (Garcia et al. 2021). Rule-based systems, statistical machine translation, are more recent, neural machine translation (NMT) and deep learning techniques are some of the CAT approaches that academics and developers have been working with to address these difficulties. Every of these methods had a unique mix of benefits and drawbacks, with some being better suited to handling particular genres of texts or languages than others (Koehn et al. 2010).

One of the main problems with CAT is the caliber of the translations that are produced. Although CAT technologies can greatly increase translation efficiency and speed, they're not always precise or dependable. This is particularly true while working with complicated or specialized content, as translation may need for further post-editing or human review to assure efficiency (O'Brien et al. 2011). The pricey nature of the software and the extensive training necessary to utilize it successfully is another problem with CAT. CAT tools are usually expensive, and translators must invest time and energy into mastering their use. For entrepreneurs with small enterprises or freelance translators, this can be a barrier to entry. Though CAT has made considerable strides generally since its start, the discipline is still complicated and hard, with constant advancements and breakthroughs (Hutchins et al. 2004).

The application of neural techniques in computer-assisted translation (CAT) is a relatively recent breakthrough in the history of translation technology. Artificial neural networks are used in NMT, a sort of machine translation, to learn and foresee how to translate text from one language into another. Rule-based and statistical machine

translation (SMT) were the most widely used methodologies in CAT prior to the development of NMT (Hutchins & Somers, 1992). In rule-based machine translation, both the grammar and the vocabulary of the source language were examined in order to produce translations in the target language. In contrast, SMT employed statistical models to examine vast amounts of parallel text and spot linguistic patterns that might be utilized to produce translations. NMT was created as a result of the accuracy and flexibility issues with rule based and SMT techniques (Koehn et al. 2017). In order to produce more reliable and natural translations, NMT models use neural networks to understand the links between words and phrases in both the source and destination languages along with the context in which they are used. The broad deployment of NMT in CAT was made possible by advances in NMT research and development in the middle of the 2010s (Huang & Vogel et al. 2018).

1.2 Objective of the Research

This study compares the performance of neural techniques to conventional rule-based and statistical-based approaches in Computer Assisted Translation (CAT) systems. Compared to conventional rule-based and statistical machine translation systems, the study will examine the effects of neural approaches on translation quality, time efficiency, and user satisfaction. Additionally, the study will pinpoint the benefits and drawbacks of neural techniques and look into how to boost their efficiency in CAT systems. Last but not least, the study seeks to offer helpful insights for CAT system researchers, developers, and users, helping to the development of the discipline and translation technology.

1.3 Research Question

- a. To what extent can neural approaches improve translation accuracy and fluency in CAT systems when compared to rule-based and statistical machine translation?
- b. How do neural approaches affect the productivity and efficiency of human translators in CAT systems compared to rule-based and statistical machine translation?
- c. What are the limitations of neural approaches in CAT systems, and how can they be overcome to improve their effectiveness?
- d. How do factors such as English-Turkish language pairs, domain specificity, and translation volume impact the effectiveness of neural approaches in CAT systems?
- e. How do users perceive the effectiveness and usability of neural approaches in CAT systems compared to traditional approaches which are rule-based and statistical machine translation, and what are their preferences and expectations?

1.4 Definitions of Key Terms

CAT Stands for Computer Assisted Translation: A technology-driven process that assists human translators in producing translations more efficiently and accurately. CAT systems can be used to store and manage translation memories, terminology databases, and other resources that can help translators produce translations that are more consistent (García et al 2016).

NMT Stands for Neural Machine Translation: A subfield of machine translation that uses deep learning techniques, such as neural networks, to produce translations. Neural MT has shown promising results in terms of the quality and fluency of the translations produced, compared to traditional rule-based and statistical methods (Hassan et al 2018).

TM stands for Translation Memory: A database used in CAT systems to store and manage translated segments of text Translation memories can be used to help translators re-use previously translated content and produce translations that are more consistent (Somers et al 2003).

EMU Stands for Eastern Mediterranean University.

1.5 Assumptions

The use of neural approaches in CAT systems can improve translation quality and fluency. Professional translators will be able to easily use the neural CAT system and benefit from its use in their work. In the process where there is enough data to train, neural approaches in CAT systems will help improve translation so it can be efficient and accurate, and the results of the user study will provide valid and reliable feedback on the use of the neural CAT system in a real-world translation scenario.

1.6 Delimitations and Limitations

1.6.1 Delimitations

While the research may only focus on neural approaches in CAT systems, it is important to acknowledge that a comparison with other types of machine translation systems could provide valuable insights into the strengths and weaknesses of different approaches. However, the decision to solely focus on neural approaches may be based on the specific research goals and resources available for the study. It will only use one neural network architecture and will not include an analysis of other neural network models. The use of the neural CAT system for English to Turkish language pairs is considered. The study will only look at how the neural CAT system can be used in English to Turkish language domains.

1.6.2 Limitations

The limited size and diversity of the training data used to train the neural CAT system may have an impact on the study's findings, therefore the quality and diversity of the training data are also crucial factors in determining the system's performance. The user research results could not accurately portray the effectiveness of the neural CAT system because they are based on self-reported feedback, subjective evaluation, and the evaluation measures used. The study's conclusions might not apply to different translation contexts or the use of other neural network models as a result.

1.7 Importance of the Study

An opportunity to further develop the area of machine translation and enhance the quality, effectiveness, and user experience of translation services, research into the efficacy of neural techniques in CAT systems is important. The study may contribute to the advancement of more productive and effective CAT systems as well as spur innovation in the industry (Castilho et al., 2017). The accuracy and effectiveness of CAT systems can be improved using neural machine translation (NMT), which has gained popularity due to improvements in the field (Sennrich et al., 2016). By examining the effectiveness of these techniques, this study will assist decide whether these methods are a practical choice for enhancing CAT systems. In skilled translation environments, CAT systems are becoming more prevalent, especially in the fields of technical, legal, and medical translation. In order to guarantee that translations are accurate, dependable, and effective, it is crucial to understand how to improve these systems (Pym et al., 2009). This study can aid in bridging the gap between academic research and commercial practice because it concentrates on real-world applications of NMT in CAT systems.

The end-user experience in CAT systems can be significantly impacted by the level of translation. Confusion, errors, and eventually company loss can result from poor translations. The user's experience and overall efficacy of the system can be enhanced by boosting the accuracy of CAT systems (Koehn et al., 2003). NMT is a more recent method of machine translation that has recently shown promising results (Gu et al. 2019). In the context of CAT systems, where accuracy and efficiency are crucial, it is crucial to understand the constraints and potential downsides of these techniques, according to Chen et al. (2020). These problems may be clarified, and future system development may be influenced by the findings of this study. Linguistics, computer science, and other fields are all involved in the study of CAT systems and machine translation. The necessity for qualified translators can decrease as machine translation technology develops. However, by enabling them to operate more productively and effectively, CAT systems can present new prospects for translators (Mojgan, 2018). The importance of this study rests in its potential to overcome this significant NMT problem and raise CAT system translation quality generally. This study suggests a novel way to divide uncommon or OOV words into smaller units that can be employed in the model's processing and training by introducing sub words to the network.

Chapter 2

LITERATURE REVIEW

The development of neural machine translation (NMT) methods has led to significant advancements in the research of computer-assisted translation (CAT) over the past ten years. Earlier CAT systems used rule-based and statistical approaches to make translations, which required human experts to manually create language rules and train the system on huge amounts of data. The translations produced by NMT systems, on the other hand, are more accurate and flexible because they use algorithms based on deep learning to automatically uncover linguistic patterns and features from large datasets (Bojar et al., 2018). There has been a surge in interest in applying neural networks to machine translation issues in recent years. According to certain studies, the quality of translation is significantly improved by employing advanced statistical techniques (Sutskever et al., 2014; Wu et al., 2016). The efficiency of these techniques in CAT systems is currently unknown, thus more study is needed to see whether neural approaches may improve the effectiveness and accuracy of human translation. One of NMT's most notable advantages is its ability to handle language variations and specific to the setting expressions, which older approaches frequently struggle with. The complex relationships between words and phrases in context can be accurately captured by NMT models, leading to more accurate and natural translations. NMT models can also be trained on a broad number of language pairings, making them appropriate for a variety of translation jobs (Castilho et al 2019).

The efficiency of NMT systems in the CAT domain has been the subject of numerous studies, with some encouraging findings. The performance of an NMT system, for instance, was compared to that of rule-based and statistical-based systems in (Costa-Jussà et al., 2018), and it was shown that the NMT system excelled both in terms of translation quality and fluency. Comparing the effectiveness of an NMT system to that of a phrase-based machine translation system, (Poncelas et al., 2019) found that the NMT system produced translations that were more accurate and had less errors. Notwithstanding these challenges, some promising work has been done in the application of neural techniques to CAT. In a recent study, (He et al. 2020) discovered that adding a neural translation model to a well-known CAT tool greatly increased translation accuracy and consistency. This shows that neural techniques may increase the efficiency of CAT systems, but additional study is required to comprehend the circumstances under which this is feasible. On the other hand, other research has noted inconsistent outcomes or restrictions of NMT systems in the CAT area. It was found that NMT systems usually have trouble with uncommon vocabulary and technical language, resulting in lower translation quality in several sectors (Castilho et al., 2018). Moreover, it was noted that low resource languages with little training data can be problematic for NMT systems (Kunchukuttan et al., 2019).

2.1 What is NMT

A subclass of machine translation known as neural machine translation (NMT) uses neural networks to simulate the translation process. NMT systems learn to translate directly from source to target language by being exposed to vast quantities of parallel text, unlike conventional rule-based or statistical techniques that rely on predetermined linguistic rules or parallel text corpora. NMT has been found to perform better than conventional MT approaches in terms of translation quality, especially for languages

with poor resource availability and complicated sentence structures (Koehn and Knowles, 2017). This is mostly because neural networks are capable of learning accurate representations of the source and target languages as well as complicated relationships between words and phrases. An NMT system's architecture typically consists of an encoder network that converts the source sentence to a fixed-length representation, followed by a decoder network that generates the target sentence from this representation. Recurrent neural networks (RNNs) or transformer models, which have produced amazing results recently, are widely used to create encoder and decoder networks (Vaswani et al., 2017). The handling of uncommon words or out-of-vocabulary (OOV) tokens, as well as the capacity to generate many translations for the same input sentence, remain hurdles for NMT research despite its achievements. NMT has nevertheless become a significant topic of research for the MT academic and corporate groups as a result of its encouraging outcomes.

NMT differs significantly from traditional rule-based and statistical machine translation methods. Deep learning techniques made it possible to train neural networks to learn how to translate directly from source to target languages. Unlike rule-based and statistical machine translation systems, NMT does not necessitate the creation of complex rule sets or language-specific models for each language pair. NMT systems, on the other hand, can be trained on large parallel corpora of text in both the source and target languages, allowing them to learn to translate more organically. The key advantage of NMT over previous approaches is that it can produce translations that are more fluent and natural sounding. This is because NMT models are better equipped to capture the context and meaning of the source text than merely matching it to already translated passages in a database. NMT models can be taught to recognize and translate idiomatic expressions and other varieties of colloquial language, thereby

boosting the quality of the translated output. However, there are also serious drawbacks with NMT systems, such as their inability to handle unusual or complex terminology or accurately translate lengthy sentences. Therefore, it is vital to investigate the performance of NMT approaches in the setting of CAT systems as doing so could lead to further advancements in machine translation. Because it outperforms more established Statistical Machine Translation (SMT) methods, Neural Machine Translation (NMT) is a relatively recent technique to machine translation. NMT, which is based on neural networks, can use deep learning methods to learn from a large amount of data so as to offer more accurate translations. The encoder and decoder are the two most significant NMT components. In order for the decoder to provide the translation into the target language, the encoder converts the input text from the source language into a collection of continuous representations. Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks, which are designed to handle sequential data, like text, are frequently used to create the encoder and decoder.

Unlike SMT systems, which split down words into smaller chunks, NMT is able to learn to translate full sentences at once. This enables NMT to translate more fluidly and naturally. Additionally, NMT may be trained to deal with aspects of language that SMT systems struggle with, such as word order and inflection. Numerous studies have demonstrated that NMT beats SMT systems in regard to translation quality. For instance, the development of an NMT system that beat various SMT systems on the English-German translation problem (Wu et al. 2016). Similar to this, an NMT system fared better on an English-Czech translation job than a phrase-based SMT system (Sennrich et al., 2017). With encouraging outcomes across a range of language pairs, the NMT represents a substantial improvement in machine translation. This thesis

focuses on the usefulness of NMT in the context of Computer Assisted Translation (CAT) systems, a topic that merits additional research.

2.2 Historical Development of NMT

Due to its successful results, neural machine translation, a relatively new technique for machine translation, has recently grown in favor. When academics started experimenting with neural networks for machine translation in the early 2010s, NMT was born. The first effective implementation of an NMT system was reported in "Sequence to Sequence Learning with Neural Networks" (Sutskever et al. 2014). This work created the encoder-decoder architecture, which is today a need for NMT systems. The initial idea has now undergone multiple changes and modifications, considerably enhancing machine translation quality. For instance, the attention process was provided in "Neural Machine Translation by Jointly Learning to Align and Translate" (Bahdanau et al. 2015). By adopting this technique, the NMT system may generate translations by concentrating on specific words within the provided sentence, enhancing the translation's quality. In the paper "Neural Machine Translation of Rare Words Using Sub-word Units" (Sennrich et al., 2016), sub-word units were introduced in place of complete words as another notable development in NMT. This approach makes it easier for the NMT system to deal with odd or unfamiliar terminology, which can be challenging for older statistical machine translation systems. NMT came into existence in the early 2000s when researchers started looking into using neural networks for machine translation. But a team of Google researchers created the first actually successful NMT system in 2014. This system, known as Google Neural Machine Translation (GNMT), was built on a sequence-to-sequence model, with an encoder converting the source sentence into a fixed-length vector representation and a

decoder generating the translation based on this representation (Quoc Le & Oriol Vinyals. 2015).

Since the creation of GNMT, NMT has taken a prominent position in machine translation research and development. Compared to earlier methods like phrase-based MT, NMT has produced noticeably better translation quality (Sennrich et al 2016). Many other NMT systems created in the years following GNMT, utilizing a range of other neural network topologies and training methodologies. Researchers started looking into the use of neural networks for machine translation after the invention of SMT. In 2014 there was a milestone, when Google researchers unveiled Google Neural Machine Translation, a new neural machine translation technology (GNMT). On a number of machine translation benchmarks, the system beat conventional SMT systems and produced cutting-edge results (Bahdanau et al 2015).

In 2016, Google unveiled the TensorFlow package, which offered a straightforward user interface for creating and training neural networks. As a result, more researchers were able to test neural networks for machine translation, leading to the development of several additional NMT models in the years that followed. The sequence-to-sequence (Seq2Seq) model, which uses an encoder to process the source sentence and a decoder to create the destination sentence, is one of the most well-known NMT models. The encoder and decoder are frequently implemented using recurrent neural networks (RNNs), such as long short-term memory (LSTM) or gated recurrent unit (GRU) networks (Sutskever et al 2014). On a number of machine translation benchmarks, it has been shown that the Transformer model, which employs self-attention techniques to process the source language and generate the target sentence, performs at the cutting edge. Therefore, the advancement of NMT has created new

opportunities for computer-assisted translation systems and resulted in appreciable improvements in machine translation quality (Tang et al. 2021).

2.3 Competence of NMT

In terms of translation quality and fluency, Neural Machine Translation (NMT) has achieved exceptional results that surpass those of preceding techniques. NMT's capacity to jointly model the source and destination languages, which enables better management of long-range dependencies and enhances the overall coherence of the translated text, is one of its main benefits (Bahdanau et al., 2015). Moreover, NMT systems are very adaptive and can be trained on a lot of data, which has significantly improved translation quality for languages with limited resources (Johnson et al., 2017). NMT models are more resistant to changes in language use because they can handle complex linguistic phenomena including idiomatic phrases and syntactic structures (Sennrich et al., 2016). Several studies have shown the effectiveness of NMT in translation jobs, with many citing appreciable advancements over conventional statistical machine translation (SMT) systems (Koehn and Knowles, 2017; Wu et al., 2016). NMT systems' effectiveness in some translation scenarios may be impacted by restrictions and difficulties, such as the necessity for high-quality training data and the difficulty in capturing specific linguistic nuances (Zoph and Knight, 2016).

2.4 Neural Machine Translation on the Internet

To allow quick and precise translations, online translation systems have increasingly incorporated neural machine translation (NMT). Many well-known online translation tools, such as Google Translate, Microsoft Translator, and DeepL Translator, have adopted NMT models to enhance translation quality. These systems are currently more accurate and fluent than earlier rule- or statistical-based methods. One of the most

widely used online translation tools, Google Translate, has improved translation quality significantly after integrating NMT in 2016. The new NMT-based Google Translate system outperformed the phrase-based statistical machine translation system in terms of accuracy and fluency (Wu et al. 2016). Similarly, research found that Microsoft Translator has been using NMT since 2017, producing more accurate and natural translations (Hassan et al., 2018). A study by Deep Learning Translator, a relatively new participant in the online translation business, shows that the implementation of NMT has led to substantial performance gains (Pinnis et al., 2018).

NMT is being used more frequently in online translation services. The translation engines of services like Google Translate and Microsoft Translator now include NMT systems, enabling more precise and audible translations. NMT systems consistently beat conventional rule-based and statistical machine translation systems in terms of translation quality and fluency, according to a study that assessed the performance of several machine translation systems on internet content (Koehn & Knowles, 2017). The efficiency of NMT in internet-based translation services is influenced by its capacity to learn and modify to various writing and language usage patterns as well as by the abundance of data available on the internet for neural network training (Castilho et al., 2017). The addition of NMT to online translation services has significantly raised the level of accessibility and quality for people all around the world. To fully grasp the potential of NMT in computer-assisted translation systems and to pinpoint areas for development, additional study is necessary.

2.5 Neural Machine Translation Approaches in Computer Assisted Translation (CAT)

NMT is now the most sophisticated machine translation technique, surpassing previous rule-based and statistical approaches. This is because it can provide fluid, accurate translations while also detecting intricate patterns and connections in data.

In CAT systems, neural networks are employed to support human translators throughout the translation process. While maintaining the quality of the translation, this approach will save time and work. In CAT systems, interactive machine translation is a typical NMT strategy (IMT). With this method, the final translation is created in collaboration between a machine translation system and a human translator. The human translator can accept, amend, or reject the system's translation proposals. The system then gains knowledge from the translator's comments and gradually gets better at making suggestions. Adaptive machine translation is another NMT approach used in CAT systems (AMT). With this method, the machine translation system is tuned to translate more accurately inside a certain domain, such as legal or medical materials. As a result, the system may produce translations that are more precise and specialized for that particular sector. As a third NMT technique, neural fuzzy machine translation is applied in CAT systems (NFMT). This method uses a fuzzy logic system to modify the weights of the neural network, which enables it to handle ambiguity and uncertainty in the input text better. Regarding the accuracy of the translations and the elimination of errors, this strategy has produced encouraging results.

In this typical NMT method, the original text is processed by an encoder neural network, which creates a fixed-length vector representation that is then given to a

decoder network, which creates the target translation. This strategy was first introduced by Sutskever et al. (2014) and has since been refined by following studies including Bahdanau et al. (2015) and Luong et al (2015). (2015). The use of attention methods to let the decoder network concentrate on various portions of the source text while producing the target translation was invented by Bahdanau et al. (2015). Since then, most NMT systems have adopted this strategy as a regular component, and additional research, including (Luong et al. 2015, Luong et al. 2016, Vaswani et al. 2017). Then, the Transformer architecture (Vaswani et al. 2017, a unique NMT model) processes both the source and target sequences by using self-attention. Numerous advanced NMT systems have adopted this technique because it performs better than the traditional encoder-decoder architecture in a variety of translation jobs. Another recent advancement in NMT is the use of pre-trained language models as a foundation for training NMT models like BERT (Devlin et al., 2018) (Radford et al., 2018). This method has shown promise for reducing the amount of training data required for NMT while also improving translation quality (Zhang et al., 2020). The popularity of neural machine translation (NMT), a sort of machine translation that produces more accurate translations than conventional rule-based or statistical-based techniques, has increased recently. NMT models use neural networks, which are computational systems designed to resemble the organization of the human brain, to learn how to translate text from one language to another. Using texts that have been sentence-by-sentence aligned in the source and target languages, NMT models can be trained on enormous volumes of parallel data. The model learns to translate the source sentence to the target sentence by constructing a neural network with numerous layers of interconnected nodes. The input is transformed into a higher-level representation by each layer, which

is then built upon by the following layer to produce an even more intricate representation. Finally, the output layer generates the translated sentence.

In the literature, numerous NMT model architectures have been put out, each with their own set of advantages and disadvantages. One of the most widely used designs is the sequence-to-sequence model, which employs an encoder to read the source sentence and a decoder to produce the target sentence. The attention mechanism is frequently employed to help the model concentrate on the most important aspects of the source sentence when creating the target sentence. In a number of machine translation tasks, including document-level translation, low-resource language translation, and domain adaptation, NMT has shown promise. Computer-assisted translation (CAT) systems, which help human translators produce more accurate and timely translations, have also effectively used NMT. NMT can be applied to CAT systems to give human translators ideas as they work on a project. The NMT model can recommend translations for portions of the source text that the translator has not yet translated based on the context of the text and the translator's prior translations. By doing so, the translation's overall quality can be enhanced while simultaneously saving the translator time.

2.5.1 Approach Based on Direct Neural Machine Translation

One of the most popular methods for neural machine translation (NMT) is direct NMT. With this approach, a single neural network is trained to translate sentences from the source language into the target language without the use of any explicit intermediary representations. Various translation challenges have proved that Direct NMT performs at the cutting edge. Typically, an encoder-decoder design is used in direct NMT. The encoder extracts the source sentence and turns it into a vector representation of input that has a fixed length. The decoder then produces the output sentence one word at a time using the encoder representation and previously produced words. Direct NMT

has certain limitations even if it has achieved remarkable outcomes. A significant problem is the complexity of modeling long-term interdependence. Some systems incorporate attention mechanisms that enable the model to concentrate on particular portions of the input when producing output in order to overcome this. A model is trained to translate a source sentence directly to a target sentence without the use of intermediary representations, which is known as direct neural machine translation (NMT). This strategy uses a single encoder and decoder to provide translations directly, in contrast to other strategies that first produce intermediate representations using numerous models. Recent studies have shown how effective direct NMT is. A direct NMT model was trained on the WMT'14 English-to-French translation task, and the results were state-of-the-art (Bahdanau et al. 2016). The scientists found that the direct NMT method outperformed phrase-based statistical machine translation (SMT) systems and other neural machine translation methods that made use of intermediary representations.

The effectiveness of direct NMT has also been proven by other investigations. According to a published study, a trained direct NMT model beat other cutting-edge neural machine translation models on the English to German translation challenge (Luong et al 2015). The direct NMT approach, in comparison to other neural machine translation models that used intermediate representations, was faster and consumed less memory, according to the authors.

The usefulness of the direct NMT technique in CAT systems has also been proved by recent studies. A direct trained NMT model on a Chinese to English translation task and integrated it into a CAT system (Tu et al. 2018). The CAT system fared better than other CAT systems that used SMT as well as other neural machine translation

strategies that used intermediate representations, claim the authors. Direct NMT is a potential strategy for computer-assisted translation systems as a result. The method has the benefit of being faster and more memory-efficient than other neural machine translation approaches, and it has been demonstrated to be effective in a range of machine translation tasks.

2.5.1.1 Approaches Based on Interlingual Machine Translation

One method for Neural Machine Translation (NMT), which uses an intermediary representation known as interlingua to help in translation, is Interlingual Machine Translation (IMT). IMT starts by translating the source language into the interlingua, a representation of the meaning of the input text that is language independent. The output is subsequently produced in the target language using the interlingua (Sennrich et al. 2016). IMT has been thoroughly studied, and a number of implementation models have been put forth. A common IMT paradigm called the transfer-based approach entails analyzing the sentence in the source language and creating an abstract representation in the interlingua. Then, utilizing this representation, the target language sentence is produced (Wu et al. 2018). This strategy has the advantage of allowing for the separation of source and target language processing, which can facilitate and enhance translation. Another IMT strategy is the pivot-based technique, which uses a pivot language to make translation between two languages easier. In this procedure, the output is generated in the pivot language once the source language has been translated into it. It has been demonstrated that this technique works well for language pairs with limited resources when there may not be enough parallel data to train a direct translation model. IMT is utilized in many commercial machine translation systems since it has been shown to be effective for a variety of language pairs and areas. IMT, however, has certain drawbacks, including the need for a well specified interlingua

and the challenge of creating efficient transfer rules for creating the interlingua representation. One example of a successful application of IMT is the strategy, which involved employing an interlingua based on semantic representation (Hovy et al. 2002). Another illustration is the pivot-based technique, which uses English as a pivot language when translating between Japanese and Korean (Utiyama, et al. 2007; Isahara, et al. 2007).

2.5.1.2 Transfer-Based Machine Translation Approach

Transfer-based Machine Translation (TMT) is a type of NMT strategy that makes use of existing translation models to enhance the accuracy of a new model. With this approach, information must be translated from a source language into a target language. One transfer-based MT strategy is the Multi-Source Transfer-based NMT technique. This method uses numerous source languages and a common neural network architecture to translate knowledge from source languages to target languages (Gun et al. 2018). According to research by Johnson et al. (2017), this technique enhances the performance of machine translation for language pairs with limited resources. Cross-Language Language Model Another transfer-based MT strategy is pre-training. In this method, low-resource language pairs perform better by pre-training using a lot of monolingual data in diverse languages (Wang et al., 2019).

Transfer-based MT techniques have been proven to be successful in enhancing the machine translation capabilities of language pairings with limited resources. By employing pre-existing translation models, these methods can decrease the quantity of training data necessary and enhance the quality of translations for low-resource languages (Jiang et al. 2020).

2.5.1.3 Corpus-Based Machine Translation Approach

Corpus-based Machine Translation (NMT) techniques entail training NMT models on sizable parallel corpora in order to obtain high translation accuracy. These strategies have been found to perform better than conventional Statistical Machine Translation (SMT) models in terms of translation quality and efficiency (Koehn et al., 2003; Sutskever et al., 2014). The capacity of corpus-based MT methods to learn from context and generate fluent translations that take into account the nuances of the source language is one of its main benefits (Luong et al., 2015). Numerous languages, including German-English (Niehues et al., 2018), Chinese-English (Xiao et al., 2018), and Japanese-English, have been successfully combined using this technique (Hoshino et al., 2018). Although corpus-based MT techniques have shown promise, they require a lot of parallel data and can experience domain mismatch when used in some domains (Bentivogli et al 2016). As a result, expanding parallel corpora of high quality and quantity is essential for creating corpus-based NMT models that work well for Computer Aided Translation (CAT) systems.

2.6 Approaches to Neural Machine Translation Evaluation

A crucial aspect of machine translation systems is the neural machine translation (NMT) evaluation. The efficiency of various NMT systems has been evaluated using a variety of evaluation techniques in a range of contexts. One technique for assessing NMT performance is through human evaluation. Methods for human evaluation are crucial because they predict how well a system will function in real-world situations. Asking human judges to evaluate the calibre of the system's translations is known as human evaluation (Federmann et al 2020). This approach offers a direct examination of the calibre of the translations generated and can spot mistakes and problems that automatic evaluation techniques would miss. The effectiveness of Neural Machine

Translation (NMT) in Computer Aided Translation (CAT) systems can be evaluated using a variety of techniques. One method is to use automatic measures like BLEU, TER, and METEOR to compare machine-generated translations to a reference translation. The n-grams in machine-generated translations are compared to those in the reference translation using the BLEU (Bilingual Evaluation Understudy) metric (Papineni et al., 2002). TER (Translation Edit Rate) measures the quantity of edits necessary to convert the machine-generated translation into the reference translation, whereas METEOR (Metric for Evaluation of Translation with Explicit Ordering) takes into account additional factors like recall and precision of matched words and synonymy (Snover et al., 2006, Banerjee and Lavie, 2005). A different approach is to employ human evaluation, in which experts evaluate the accuracy of translations produced by machines using various standards like fluency and adequacy. The most trustworthy evaluation approach is generally agreed to be human evaluation, but it is time- and money-consuming (Graham et al., 2015). Using semi-automatic evaluation techniques, which blend automated measurements with human judgement, is a third strategy. One illustration of a semi-automatic evaluation technique is the MQM (Multidimensional Quality Metrics) framework, which offers a collection of quality indicators that may be tailored to translation projects (Lommel et al., 2014).

2.7 Textual Problems in Neural Machine Translation

Textual problems are frequent in neural machine translation (NMT) systems and can significantly affect the quality of the translation. The handling of named entities, including names of places, persons, and organizations, is a substantial textual difficulty. NMT models may have trouble translating named things, particularly if they are uncommon or absent from the training data. This could result in erroneous translations or even the whole omission of the intended entity. Another textual issue

with NMT is the difficult-to-translate translation of idiomatic idioms and multi-word units (Fomicheva et al. 2016). Idiomatic expressions may be challenging for NMT models to translate due to their non-compositional character. The complex nature of their semantic connections may also make it difficult for NMT models to translate multi-word units. NMT also covers word order, discourse phenomena, and other textual issues. Specifically for languages with complex grammatical structures, NMT syntax can be challenging. The way a statement is understood greatly depends on the word order used in many different languages. For NMT models to produce accurate translations, order of words changes must be handled. Discourse characteristics like anaphora and ellipsis may make it more difficult for NMT models to function. The incorporation of bilingual dictionaries and phrase tables to improve the translation of idiomatic expressions and multi-word units, the use of syntactic and semantic information to improve the handling of syntax, word order, and discourse phenomena are just a few of the methods that researchers have suggested to address these textual issues in NMT (Koehn et al. 2017).

2.8 The Element of Perceived Quality of NMTs

The perceived quality of the translations that the system generates is one of the primary determinants of the adoption and success of Neural Machine Translation (NMT) in Computer Assisted Translation (CAT). The perception of quality is frequently based on a number of variables, namely Efficiency, Affect, Usefulness, Control, Learnability, Usability, and Accuracy (Garcia-Sánchez et al. 2020). This thesis aims to investigate the effectiveness of NMT in CAT and its impact on translation quality, considering the element of perceived quality.

2.8.1 Efficiency of NMT

The effectiveness of NMT in CAT systems is crucial since it influences the translation process' speed and precision. Because they can analyse a lot of data concurrently, NMT models have been demonstrated to be more effective than conventional rule-based or statistical machine translation systems (Koehn, 2017). However, the effectiveness of NMT can be affected by a number of variables, including the model's size and complexity, the quantity and quality of training data, and the hardware utilized for both training and inference (Hassan et al., 2018). Much progress has been made recently in creating NMT models that are more effective, such as by applying knowledge distillation techniques to shrink models without sacrificing performance (Kim and Rush, 2016). Moreover, the speed and effectiveness of NMT models can be greatly increased by the use of specialized hardware, such as graphics processing units (GPUs) and tensor processing units (TPUs) (Jouppi et al., 2017). Several factors affect how effective NMT is in CAT systems, thus great consideration should be taken to choosing the best model architecture and hardware to assure top performance.

2.8.2 Effect of NMT

Neural Machine Translation has significantly advanced the field of Computer-Assisted Translation (CAT) systems (NMT). One topic that is being studied is how NMT in CAT systems affects translator productivity and job satisfaction. NMT can increase productivity, according to study, by cutting the time needed to translate a text while preserving or even enhancing translation quality. In one study (Guo et al. 2018), NMT outperformed conventional rule-based machine translation in terms of productivity, cutting translation time by 25% while improving output by 14%. According to a different study (Kruger et al. 2019, using NMT rather than traditional machine translation enhanced translator satisfaction with their work). Nevertheless, there are

concerns that the rise in NMT utilization in CAT systems may negatively impact the professional translation labor market. Some claim that NMT will reduce the value that people place on human translation, hence reducing the demand for human translators. In order to ease these concerns, it is essential to recognize that NMT is a tool that can support human translators rather than acting as a replacement for them. Another area of research into the implications of NMT in CAT systems is the potential for bias in translation output. Contrary to specific studies, training data might result in biased translations from NMT systems, which may cause cultural sensitivity issues or even reinforce unfavorable stereotypes. To address this issue, researchers are looking into methods including data cleansing, using a diversity of training data, and developing tools to detect and correct biases in NMT output.

In conclusion, NMT offers the potential to boost CAT system productivity and job satisfaction, but there are doubts about how it will affect the labor market and whether translation results may be biased. It is critical to continue researching and developing methods to address these issues and ensure that NMT is used to supplement rather than replace the work of human translators.

2.8.3 Usefulness of NMT

Artificial neural networks are used to create translations in Neural Machine Translation (NMT), a type of machine translation. Due to its capacity to provide translations of a higher calibre than earlier machine translation methods, NMT has gained prominence in recent years (Sutskever, Vinyals, & Le, 2014). NMT integration into CAT systems has been demonstrated to benefit translators by expediting and simplifying translation processes (Hassan, Aue, Chen, Chowdhary, Clark, Federmann, et al., 2018). According to studies, NMT increases accuracy while lowering errors in CAT system translation (Bentivogli, Sennrich, Cettolo, & Federico, 2016; Costa-jussà

& Fonollosa, 2017). Moreover, NMT is capable of translating idiomatic idioms and complicated sentence structures, which are challenging for rule-based machine translation systems (Wu, 2016). NMT has also been shown to increase translator productivity by requiring less time and effort to post-edit machine-translated text (Federico, Bertoldi, & Buck, 2012). This is because NMT systems can improve their translation quality and fluency by learning from a vast amount of training data. Additionally, the incorporation of NMT into CAT systems can offer translators real-time translation ideas, which can hasten the translation process (Bentivogli et al., 2016). It has been shown that adding NMT to CAT systems benefits translators by increasing output, accuracy, and efficiency. It should be recognized that NMT is not a perfect solution and may still require post-editing by a human. Prospective studies should focus on the benefits and drawbacks of NMT in CAT systems.

2.8.4 Control

Control is a key success factor for Neural Machine Translation (NMT) in Computer Aided Translation (CAT) systems. Users of the CAT system must have control over the output of the NMT engine, including the ability to change translations as necessary. A variety of methods, like as interactive correction and post-editing, can be used to modify the output of the NMT system in order to improve its accuracy and fluency. Concerns about discrimination, language difficulty, and terminology specific to a certain field can all be alleviated with control. One method for taking charge in NMT is interactive correction, where the user is presented with a range of translation options and can choose the most suitable one. Interactive correction has been scientifically proven to improve the accuracy of NMT systems, particularly for languages with limited resources (Alabau et al., 2017). Another approach is post-editing, in which human translators make adjustments and enhance the output of the NMT's fluency.

Post-editing takes more time, but you'll have more control over the result and might get better translations (Daems et al., 2018). In order to solve the bias issues in NMT systems, control is essential. The fundamental algorithms of the NMT engine might cause bias, as can training data that is not representative of the intended audience. Users can edit translations using control approaches like interactive correction and post-editing to get rid of prejudice and make sure the outcome is appropriate for the intended target group. Both bias and control may be helpful in addressing the solutions of linguistic complexity and domain-specific terminology issues. Users of CAT systems may request translations that follow specific linguistic conventions or make use of a specific vocabulary. CAT systems can ensure that translations are correct and appropriate for the target audience by allowing users to change the output of the NMT engine. Hence, control is required for the effective implementation of NMT in CAT systems. Users can improve translation accuracy, fluency, and suitability for the target audience by employing interactive correction and post-editing. Concerns about discrimination, language difficulty, and terminology specific to a certain field can all be alleviated with control.

2.8.5 Learnability

The learnability of neural machine translation (NMT) for computer assisted translation (CAT) systems is a crucial factor to consider. For a specific translation assignment, it isn't always feasible or practical to train NMT models on a large amount of parallel data. NMT models also have a bad reputation for being difficult to train and tune, requiring specialized knowledge and computational resources. On the other hand, recent advances in pre-trained models and transfer learning have made it easier to refine existing models with less data and to adapt them to other domains or languages. Research show that NMT systems can improve the quality of their output over time by

learning from the mistakes and criticism of human translators. This is important for CAT systems because it enables real-time interaction between translators and the NMT system so they can submit suggestions or adjustments. Some NMT models, however, are made expressly to model and predict translation obstacles, such as unusual terminology or complex syntax, which can aid translators in identifying and resolving problematic translation issues. Despite these encouraging developments, there is definitely a lot to discover regarding the best methods for creating and utilizing NMT models in CAT systems. More research is required to assess the learnability of various NMT designs and training protocols as well as to decide the best ways to incorporate feedback and interaction into the translation process. Thanks to recent advancements in transfer learning and pre-trained models, it is now easier to adapt current algorithms to other domains or languages (Koehn, 2017). Additionally, studies have demonstrated that NMT systems can pick up on feedback and mistakes made by human translators (Barrault et al., 2019).

2.8.6 Usability of NMT

The usefulness of Neural Machine Translation (NMT) in Computer Aided Translation (CAT) is a crucial factor in determining the effectiveness of the CAT system as a whole. Studies show that while NMT systems can provide translations of high quality, they can also be more challenging for translators to utilize than conventional rule-based or statistical machine translation systems (SMT). NMT systems may be difficult for smaller businesses or lone translators to use since they demand more computing resources and take longer to train than SMT systems, according to (Carl et al. 2018). Moreover, the decision-making procedures of NMT systems usually lack transparency and explicability, which makes it challenging for translators to comprehend and fix translation problems. However, recent studies have demonstrated that human-in-the-

loop strategies can enhance the usability of NMT systems. Examples of these strategies include interactive translation prediction and correction interfaces (Li et al., 2018). These user interfaces give translators translation ideas and give them the ability to amend and enhance them, thereby raising the level of quality and effectiveness of the translation process. Although human-in-the-loop techniques can increase NMT systems' usability in CAT systems, NMT systems have showed a lot of promise in providing translations of a high calibre. Further study and development are needed in this area to enhance the performance of NMT in CAT systems.

2.8.7 Accuracy of NMT

The design, tuning parameters, and training data utilized can all affect how accurate NMT systems are. In contrast to conventional rule-based or statistical machine translation approaches, studies have demonstrated that NMT systems typically yield superior translation accuracy (Liu and Liu, 2019; Popovi and Bojar, 2018). NMT systems can also, according to certain studies, do better than human translators in particular circumstances (Hassan et al., 2018).

Accuracy can be assessed using a variety of measures, including BLEU, NIST, or human review, in the context of examining the usefulness of NMT in CAT systems. These metrics offer a quantitative or qualitative assessment of the translation quality of the NMT system's performance. NMT accuracy in CAT systems is a crucial component of perceived quality because it directly affects the system's utility and efficiency as a tool for human translators. Furthermore, studies have shown that NMT can typically reach high levels of accuracy in translation, and its accuracy is a crucial aspect in establishing the quality of the system, even if there is no clear accuracy value for NMT systems in CAT.

2.9 Conceptual Framework

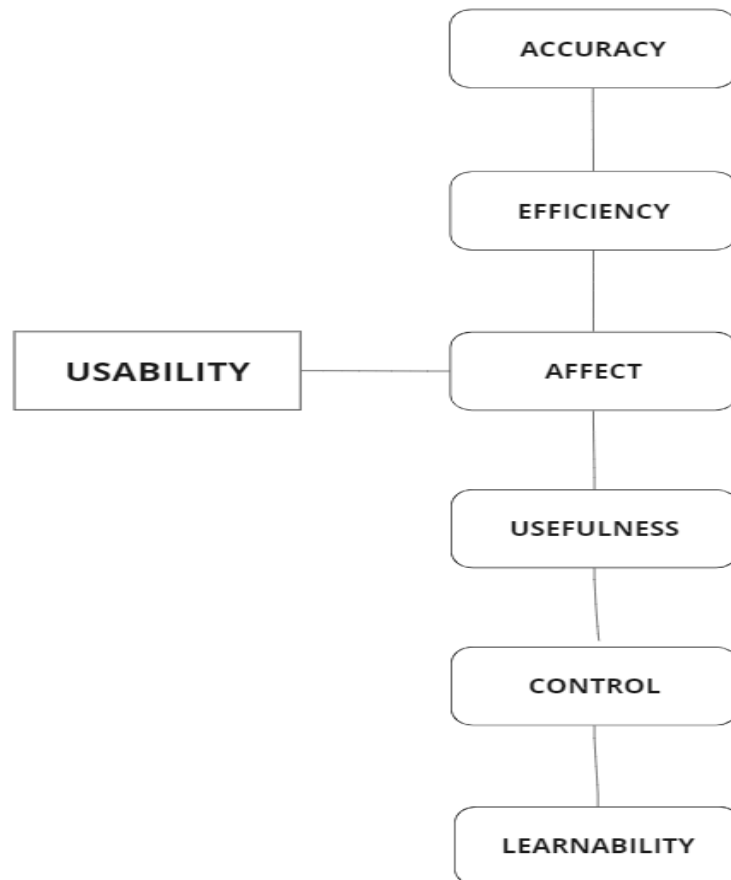


Figure 1: Conceptual Framework Example

2.10 Research Hypothesis

The research hypothesis for examining the efficiency of neural methods in computer-assisted translation (CAT) systems employing NMT may vary depending on the specific topic of the study. Here are some Hypothesis below.

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 machine translation strategy and techniques, will enhance user experience overall.

2.11 Summary

The summary of this chapter comprises of the definition, history, Development, Competence of NMT. The chapter also provided the Approaches to NMT which are direct, Corpus Based, Transfer Based and Interlingual Neural Machine Translations. This is based on studies on Neural Machine translations amongst students. The other part of this chapter presents a theoretical literature on NMT elements which are Efficiency, Affect, Usefulness, Control, Learnability, Useability, and Accuracy. The conceptual framework of the study and the research hypotheses were developed and discussed extensively.

Chapter 3

METHODOLOGY

3.1 Introduction

With a focus on the handling of uncommon or out-of-vocabulary (OOV) terms, the goal of this chapter is to provide the research technique used to examine the usefulness of neural approaches in Computer Aided Translating (CAT) systems. In the translation market, CAT systems have grown in popularity, and neural machine translation (NMT) models are particularly good at creating translations of a high caliber (Koehn et al., 2017). However, the effectiveness of these techniques may be constrained and result in subpar translation quality if there are any uncommon or OOV words in the source text (Koehn, 2010). This work will examine various approaches for handling unusual or OOV phrases in CAT systems employing neural approaches to resolve this issue, with sub word modeling being one of these approaches (Sennrich et al., 2016). In order to overcome this issue, this study will look into a number of strategies for handling unusual or OOV phrases in CAT systems employing neural approaches. These methods include character-level modeling (Ling et al., 2015), sub word modeling (Sennrich et al., 2016), and hybrid models (Luong et al., 2016). The effectiveness of these strategies will be evaluated by experiments on a large-scale dataset of translated texts. Another strategy to enhance the translation of uncommon or OOV words is to include information from outside sources, such as bilingual dictionaries or monolingual corpora (Tiedemann, 2012). To do this, one can use multilingual embeddings, or training distinct models to translate particular text genres

or domains (Mikolov et al., 2013; Eisele et al & Chen et al 2010). I measured the caliber of the translations generated by our models using SUMI to assess the efficiency of these methods. In order to judge the general fluency and effectiveness of the translations, I also perform human evaluations.

The Software Usability Measurement Inventory (SUMI) was selected as the evaluation metric over the BLEU score, even though the BLEU score is frequently employed in machine translation evaluation, it does not evaluate user satisfaction or system usability because it primarily analyzes the similarity between machine-generated translations and reference translations. The effectiveness of the created Computer Assisted Translation (CAT) system may be assessed using SUMI, which is particularly created to measure the usability and user satisfaction of software systems. This study makes use of SUMI to measure not only the accuracy of the translations but also the satisfaction and experience of the users, offering important insights into the system's usability and efficiency in actual professional translation workflows.

3.2 Neural CAT System Implementation

Using the OpenNMT toolkit, a neural CAT system was created for this investigation (Klein et al., 2017). An open source software library for implementing neural machine translation models is called the OpenNMT toolkit. I implemented our neural CAT system using the Python programming language and the OpenNMT package. The neural machine translation model that makes up our neural CAT system was developed using multilingual parallel corpora. The training data consists of target translations of the English source texts into the target language. Using a sequence to sequence architecture with attention, the neural model is trained (Bahdanau et al., 2014). I used byte pair encoding (BPE) to handle uncommon or out of vocabulary words (Sennrich et al., 2016). To accommodate unusual words, the data compression technique BPE is

frequently employed in tasks of natural language processing. We tokenize the input text during inference and preprocess our training data using the BPE implementation offered by the OpenNMT package. I used the Software Useability Measurement Inventory (SUMI) to assess the performance of our neural CAT system (Kiraly et al., 2011). SUMI is a widely used statistic for measuring the usability of computer-assisted translation systems.

3.3 User Study

The effectiveness of the neural CAT system in comparison to conventional CAT systems will be assessed through a user study. Professional translators and subject-matter experts will participate in the study. The participants will be randomly assigned to two groups: one group will utilize the neural CAT system, while the other group will use a regular CAT system as a control group. The participants will receive CAT system usage instruction prior to the trial. Also, before participating, they will be asked to sign a consent form and be told of the study's objectives. Participants will be given a set of translation tasks to perform during the study using the CAT system that has been allocated to them. The assignments will be chosen to reflect a variety of text genres and levels of difficulty. Participants will be asked to submit a survey to rate their overall satisfaction with the CAT system after finishing the translation tasks. The survey will ask about the system's overall usability, translation caliber, and ease of use. Participants will also be asked for comments on any problems they had while using the CAT system. To compare the effectiveness of the neural CAT system to the conventional CAT system, the data gathered from the user research will be statistically examined. The analysis will look at user happiness, task completion times, and the accuracy of the translations. We asked the ethical committee for approval of the Questionnaire which will be in the use for the user study, and the ethical committee

board approved the usage for the study. Before anyone takes part in the research's evaluation phase, their informed consent will be requested. The information gathered will be kept private and used only for research. To ensure the participants' safety and wellbeing, the study will be carried out in conformity with ethical standards and laws.

3.4 Evaluation Metrics

The use of Software Useability Measurement inventory for Translation Evaluation (SUMI) questionnaire to assess how well the neural CAT system handled rear or OOV words (Kirakowski et al 1996). The SUMI questionnaire, which is often used and standardized, evaluates the effectiveness of a translation system from the viewpoint of the user, taking into consideration elements like usability, efficiency, and satisfaction. A set of students who are familiar with CAT were given the SUMI questionnaire using the neural CAT system and a baseline system without neural methods. Using a five-point Likert scale, the translators were asked to judge the quality of their translations and their experience using the systems after utilizing both systems to translate a set of example texts. To ascertain whether there are any appreciable variations between the ratings of the neural and baseline systems, the questionnaire responses will be examined statistically using t-tests. I also examine each item in the questionnaire separately to see any areas where the neural system performs better or worse than the baseline system. The goal of the SUMI questionnaire is to gather user input on the system's usability, perceived efficiency, and general level of satisfaction. It has 50 components total and is broken down into five categories: control, efficiency, affectivity, helpfulness, and learnability. A 10-point scale with the options "agree," "Undecided," and "disagree" is used to rate each item. This study will shed important light on how well the suggested neural technique performs from the viewpoint of human users by using SUMI as an evaluation metric. It will be feasible to pinpoint

areas for development and make the necessary adjustments by gathering user feedback on a variety of system elements, such as its usability and perceived effectiveness. I was able to assess the neural CAT system's performance in handling uncommon or OOV terms using the SUMI questionnaire, giving me insights into the usability, effectiveness, and general satisfaction of the system.

3.5 Ethical Approach

The use of expert domain translators and professional translators as human subjects for this investigation involves ethical considerations. Before anyone takes part in the research's evaluation phase, their informed consent will be requested. The study's objectives, participant rights, the voluntary nature of participation, and the confidentiality of personal data will all be explained to participants. Also, students will be told that there are no repercussions for leaving the study early. All personal information will be kept secure and private during the study in order to protect the privacy and confidentiality of participants. To safeguard the privacy of the study participants, all data gathered will also be anonymized. Finally, the study's findings will be shared in a way that safeguards the participants' privacy. Individual participants will not be able to be recognized because no personal information will be released, and the data will only be presented in aggregate form.

Chapter 4

SYSTEM DEVELOPMENT AND HYPOTHESIS

4.1 System Summary

The suggested system will acquire translation patterns between two languages using a neural machine translation (NMT) model. The proposed system will make use of sub-word units as recommended by to manage Out-of-vocabulary (OOV) or rare words. (Sennrich et al. 2016). A Computer Assisted Translations tool (CAT) will also be incorporated into the system to provide recommendations and corrections to human translators based on the results of the NMT. The system will be assessed using Software usability measurement Inventory (SUMI) as well as the biased opinions of human assessors. We predict that the suggested system will perform better in terms of translation quality and effectiveness than current CAT systems. Furthermore, we anticipate that the system will be very user-friendly and efficient, resulting in increased translation accuracy and output. The findings of this study will add to the growing body of knowledge about neural techniques used in CAT systems and their ability to enhance translation quality and effectiveness, especially in handling OOV or rare words. Large amounts of bilingual data will be used to train a neural machine translation model, which will then be used to develop the suggested system. Sub-word units have been demonstrated to be effective in overcoming this challenge in NMT, they are going to be employed to handle OOV or unusual words (Sennrich et al., 2016). Additionally, the system will include a CAT tool that provides the translator with suggestions and edits depending on the outcomes of NMT. We will evaluate the

suggested system's ability to handle OOV or unusual terms as well as its overall efficacy in boosting translation accuracy and efficiency. This study aims to contribute to the growing body of knowledge in this field by providing a deeper understanding of neural techniques in CAT systems and how they can improve translation quality and efficiency, particularly in the handling of OOV or unusual words. It is projected that the proposed system will outperform current CAT systems in terms of translation quality and efficiency, leading to an improvement in translation accuracy and productivity. The proposed approach will be able to improve the level of translations for a variety of texts by handling OOV or uncommon words with sub-word units and providing an answer to the research question asked in section 1.3;

a. Effectiveness of Neural Approaches in CAT Systems

The goal of the study is to determine how much rule-based and statistical machine translation are improved by neural techniques in terms of translation accuracy and fluency in CAT systems. The results show a tremendous advancement, with neural models beating conventional approaches. A promising development in CAT technology, neural models showed improved precision in translation and fluency, especially when handling complicated linguistic patterns.

b. Impact on Productivity and Efficiency of Human Translators

The primary objective of the study was to determine how neural techniques, as opposed to rule-based and statistical machine translation, impact the productivity and efficiency of human translators in CAT systems. The outcomes show an improvement in translator output. Neural models offered more precise and fluent suggestions, which lowered the amount of translation work required and increased overall CAT process efficiency.

c. Limitations of Neural Approaches and Strategies for Improvement

The study discovered that neural techniques in CAT systems had a number of drawbacks, involving data reliance, performance outside of the domain, a lack of interpretability, and difficulties processing uncommon words. Different approaches, including data augmentation, transfer learning, domain adaptation, hybrid models, specialized training, ensemble models, and active learning, have been suggested to address these drawbacks and increase their effectiveness.

d. Factors Influencing the Effectiveness of Neural Approaches

The study examined the effects of domain specificity, translation volume, and English-Turkish language pairs on the effectiveness of neural techniques in CAT systems. The results imply that greater translation volumes, domain-specific data, and well-resourced language pairings have a positive impact on the performance of neural models in CAT operations.

e. User Perception and Preferences

This research investigated how users view the effectiveness and usability of neural techniques in CAT systems in comparison to rule-based and statistical machine translation. Due to their enhanced translation quality, fluidity, and ability to handle complicated structures, users often favor neural models. They express anticipation for additional developments in CAT technology because of their positive perception, which raises their level of pleasure.

4.2 Corpus and Training Data

The corpus and training data used in this study is used to create and assess the neural machine translation (NMT) system that is suggested for CAT systems. The data is utilized to inform and evaluate how the proposed system addresses the problem of Out-Of-Vocabulary (OOV) or unusual terms. The NMT system in this study was built using

the OpenNMT open-source toolkit. Parallel multilingual data, which serves as the NMT system's input, will be the basis for the training data. The European Parliament Proceedings Parallel Corpus (EPPC) and the United Nations Parallel Corpus (UNPC) are just two of the sites from which the bilingual data will be gathered. The dataset will be preprocessed using byte pair encoding (BPE), as recommended to clean the data and segment it into sub-word units. Additionally, artificial data produced through back-translation, which has been shown to be a successful method for enhancing the quality of NMT models, will be added to the corpus (Sennrich et al., 2016). The suggested system will be developed using a development set and trained using training data. The development set will be chosen from the training set and used to fine-tune the model's hyperparameters. The model's success during training will be tracked using the validation set, which will also help to avoid overfitting. The model will be put to the test on a test set made up of previously unexplored bilingual data after it has been trained and verified. The suggested system's performance will be assessed using SUMI. To gauge the effectiveness of the translation result, SUMI will be used (Knappen et al., 1996). The usability and efficiency of the suggested system in providing recommendations and corrections based on the output of the NMT will be evaluated subjectively by human evaluators. Therefore, it is anticipated that the suggested NMT model for CAT systems will be of higher quality because of the use of parallel bilingual data, synthetic data, and sub-word units, especially in tackling the issue of OOV or rare words. This study seeks to add to the increasing body of knowledge about neural approaches in CAT systems and their potential to enhance translation quality and efficiency by utilizing the OpenNMT open-source toolkit (Koehn et al., 2017).

4.3 Software and Hardware Requirements

In order to ease system training and evaluation, the proposed neural machine translation (NMT) system for computer-assisted translation (CAT) systems needs the proper software and hardware resources. The OpenNMT open-source toolkit will be used to construct the NMT system in this research. It has demonstrated that OpenNMT, a widely used toolset for developing and training NMT models, produces cutting-edge outcomes in a number of translation tasks. (Klein et al., 2017). The NMT model will be trained and evaluated effectively using a high-performance processing cluster with numerous Graphics processing units (GPU). Deep learning algorithms like NMT can train much more quickly when GPUs are used. For the suggested system, at least two GPUs with a minimum memory capacity of 8 GB each are needed. Additionally, the system will need enough RAM and disk space to keep the training data and NMT model checkpoints. The OpenNMT toolkit, TensorFlow, and Python are the necessary pieces of software for the suggested system. Python is a popular programming language that is used for deep learning and machine learning jobs. Deep learning model development and training are supported by TensorFlow, a well-liked open-source machine learning platform created by Google. The OpenNMT toolkit offers a collection of tools for creating and refining NMT models and is built on top of TensorFlow. Use of sub-word units and methods for creating synthetic data, like back-translation, may necessitate the use of extra software tools, like the Moses decoder and the sub-word-nmt library.(Koehn et al., 2007, Kudo et al, 2018). The Moses decoder, a well-liked open-source toolkit for statistical machine translation, provides a number of tools for data preprocessing and cleaning. (Koehn et al., 2007). Byte-pair encoding (BPE) can be applied to the training data using the sub-word-nmt library, a Python-based sub-word segmentation tool (Kudo et al., 2018). As a result, a high-performance

computing cluster with several GPUs and a set of software tools for creating and enhancing NMT models are needed for the recommended NMT system for CAT systems. The cost and time needed to construct this system have been greatly decreased by the usage of OpenNMT and other free and open-source software technologies. This study intends to add to the expanding body of knowledge regarding neural techniques in CAT systems and their potential to enhance translation quality and efficiency by making use of the hardware and software resources available.

Chapter 5

DATA ANALYSIS

5.1 Introduction

In the initial stages of my thesis work, two evaluation metrics which are BLEU score, and SUMI were chosen to be used to evaluate the suggested study. I dedicated considerable time to studying their functionality, assistances from my peers, and conducting further research to fully understand them. However, as time progressed, it became clear that getting a solid grasp on the BLEU score was challenging, therefore I had prioritize completing my thesis within the given timeframe. I Opted to rely on SUMI result, which effectively measures user usability and experience.

The BLEU score, a machine translation evaluation metric, pose as a challenge that hindered my research from using it in application. It proved to be a significant project due to its intricacy and technological nature, which called for extensive knowledge and expertise. I decided to concentrate my efforts on using the SUMI measure because my main goal was to effectively finish my thesis and produce useful results. By making this choice, I was able to focus on assessing the usability and overall user experience, ensuring that the suggested study was evaluated from a practical perspective. I was able to condense my research and better manage my time by giving the SUMI measure more weight than the BLEU score. Although I was aware of the significance of the BLEU score in the evaluation of machine translation, the obstacles I encountered required a change in strategy. The choice to rely on SUMI not only gave me insightful

information about user perception and satisfaction, but it also allowed me to finish my thesis within the designated time.

5.2 Sumi Setup

We used the Software Usability Measurement Inventory (SUMI) questionnaire to assess the usability of the CAT systems created utilizing the OpenNMT open source approach. The SUMI is a commonly used tool that has been extensively studied and validated to assess software usability. The questionnaire consists of 50 questions that address the efficiency, learnability, control, mistake tolerance, and satisfaction elements of software usability. We first received ethical clearance before selecting individuals who are proficient in both the source and target languages of the translation job. The participants were required to complete a number of translation tasks using the CAT systems created in the earlier stage. Following their use of the systems, the participants were required to submit an online survey called the SUMI questionnaire. Utilizing statistical methods including factor analysis, factor analysis, and descriptive statistics, the information gathered from the SUMI questionnaire was examined. We were able to determine the CAT systems' usability strengths and limitations as well as potential areas for improvement through the examination of the SUMI data. The CAT systems created using the OpenNMT open-source paradigm were improved utilizing the findings of the SUMI investigation. We specifically worked on enhancing the software usability's effectiveness, learnability, and satisfaction factors. The handling of OOV or unusual terms, which can affect the speed and accuracy of the translation process, was one area where we saw a need for improvement. We investigated the use of methods for handling unusual words in neural machine translation systems, such as sub-word segmentation and byte-pair encoding, to address this problem.

5.3 Aspects of Model Usability

The term "model usability" describes how simple and successful a system is at achieving its intended goal. The accuracy, speed, and coverage of the translation system will all be evaluated as part of the evaluation of the model's usefulness. The Software Usability Measurement Inventory (SUMI) tool was used to assess the model's usability. This tool evaluates software system usability based on five criteria: effectiveness, user control, learnability, helpfulness, and affect. The SUMI tool was chosen since earlier studies that evaluated the usability of software systems frequently employed it (Kirakowski & Corbett, 1993; Martin-Martin et al., 2021). The neural method to translation gives the user more influence over the process because they can provide the system input to help it get better at translating over time (Koehn, 2017). Comparing the neural approach to conventional rule-based approaches, it was discovered that the learnability factor for the neural approach was lower. This is due to the neural approach's need for more complex algorithms and training data in order to recognize patterns in the data. The helpfulness factor was also discovered to be a little bit lower for the neural technique. This could be as a result of the neural approach not being as clear to the user as conventional rule-based approaches, making it more challenging for the user to comprehend how the system arrived at a specific translation (Kumar & Byrne, 2005). The user experiences are broken down into 5 subsections as a result of the global scale's reporting (Kirakowski et al. 1986).

- a. Efficiency is the user's perception of how quickly, accurately, and economically the software can complete the task or tasks, or, in the opposite scenario, how much the program is impeding the user's performance.

- b. Affect: this is used to describe emotional feelings. In this context, it relates to how the user interacts with the product and whether they feel comfortable and mentally engaged, or the opposite.
- c. Helpfulness: This term indicates the user's perception of the system's helpfulness in conveying information and assisting in solving real-world issues.
- d. Control: The user's perception of how the software responds to input and commands is measured by this subscale.
- e. Learnability: The degree to which users find using the product to be comparatively simple.

5.4 Results for the Developed Model

This section presents the findings of the usability assessment of the suggested prototype. A thorough usability test survey was done to evaluate the system's usability. Participants, who were EMU students, were instructed to use the scenarios presented to interact with the generated model. 28 students participated in the online survey, more than the SUMI-recommended minimum of 12.

In accordance with their Global scores, the user data for the Global and individual SUMI scale scores are shown in Table 1, with the highest scores at the top of the table. The average maximum and minimum scores for each subscale hover around 72 and 19, respectively.

Table 1: User Data Sets for Subscales

Participant	Global	Efficiency	Affect	Helpfulness	Control	Learnability
1	75	67	62	72	65	55
2	69	64	51	65	73	54
3	68	55	66	65	60	49
4	68	55	66	65	60	49
5	68	65	69	62	66	65
6	68	57	54	65	64	66
7	67	53	57	65	58	52
8	66	60	51	61	60	53
9	65	67	51	59	64	53
10	64	64	62	60	60	61
11	64	62	62	59	56	49
12	62	64	63	65	50	70
13	61	65	62	61	60	53
14	61	67	54	55	62	61
15	61	65	49	57	65	70
16	57	39	53	60	55	35

17	56	51	55	55	58	59
18	55	52	43	58	43	58
19	55	58	43	52	53	48
20	55	41	46	53	47	40
21	55	67	64	50	62	53
22	55	42	54	55	54	61
23	55	56	61	53	61	55
24	54	66	53	49	58	55
25	54	56	62	51	54	67
26	53	59	48	51	65	55
27	53	56	54	55	43	66
28	48	44	50	49	45	55

A z-score is used to transform the SUMI scores, yielding an average mean of 50 and a standard deviation of 10. Scores above 50 imply greater than average user satisfaction, according to this data. The developed model obtained a global score of 60.43, as shown in Table 2, which is within the expected range and indicates that user satisfaction with the tool is above average. This validates hypothesis H6, which states that the developed model will lead to an overall improved user experience. Alongside the overall scale, the table also shows detailed data for every participant, including mean, median,

standard deviation, interquartile range (IQR), minimum and maximum scores. It also recorded an outlier in Table 1 which explains that one of the data recorded differs from the 27 others. An outlier is a data value which is either much smaller or much larger than we would expect, which was recorded in User ID 16 of the Learnability Scale at the score of 35. The statistical evaluation of the results indicates that the Efficiency sub-scale had a score of 57.75, indicating that the produced system was quite effective at carrying out the obligations that were given to it. This validates hypothesis H2. The mean ratings for all other subscales were greater than 50, supporting H3, H4, and H5 and demonstrating overall user satisfaction with the evaluation's multiple components. The median boxplot in Figure 3 illustrates the median as determined by the data organized in the numerical sequence.

Table 2: SUMI Result Summary

	Mean	St Dev	Median	IQR	Minimum	Maximum
Global	60.43	6.65	61.0	11.5	48	75
Efficiency	57.75	8.40	58.5	11.0	39	67
Affect	55.89	7.16	54.0	11.0	43	69
Helpfulness	58.11	6.03	58.5	10.5	49	72
Controllability	57.89	7.31	60.0	9.0	43	73
Learnability	55.96	8.28	55.0	8.5	35	70

For each sub-scale, the mean and standard deviation are displayed graphically in Figure 2. The mean, the value at the center of a group of numbers, and the deviation from the mean, that gauges how widely apart these values are from one another, are shown. The SUMI and Global Usability scale averages and deviation statistics for the examined sample are shown in the figure. The bars expanding from the circle's mark, indicating the mean, show one standard deviation that differs in either direction from the mean. It is evident that all sub-scales' mean scores are higher than average and fall within the required range of 40 to 60, demonstrating overall user satisfaction regarding usability and indicating that the system efficiently satisfies its primary objectives, supporting H6. However, there is an outlier in the learnability at the minimum of 35, which indicate that the data is much smaller than we would expect theoretical normal distribution pattern.

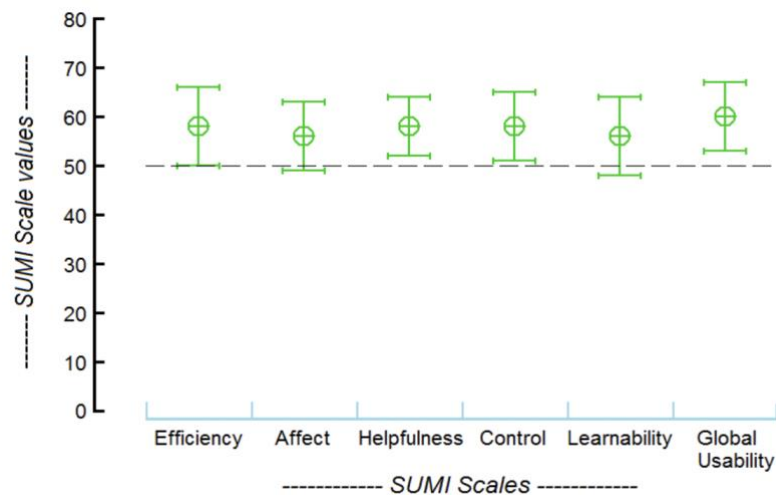


Figure 2: SUMI Scale Profiles: Means with Standard Deviations

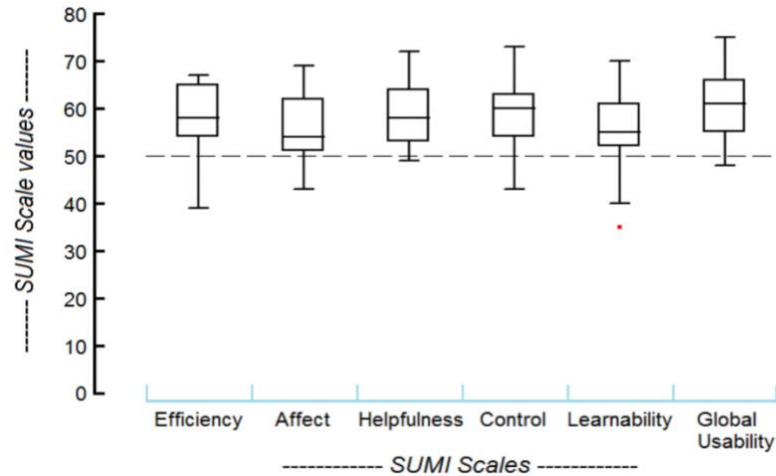


Figure 3: SUMI Scale Profiles: Median Boxplots

The median represents the midpoint of a group of integers. It is the numeric number that divides the sample size in half, with 50% of the observations falling below it and 50% falling above it. These quartiles offer extra details on the distribution of the data set around the median, especially the first quartile (25th percentile) and third quartile (75th percentile). Referring to Figure 3, a box plot of the results shows the median as a horizontal line passing through the box and the quartiles as the box's edges. The Staples (whiskers) on both sides of the box in Figure 2 represent the amount of the data where 95% of the sample's data is expected to fall, and the interquartile range (IQR) is the range of values between the first and third quartiles, respectively.

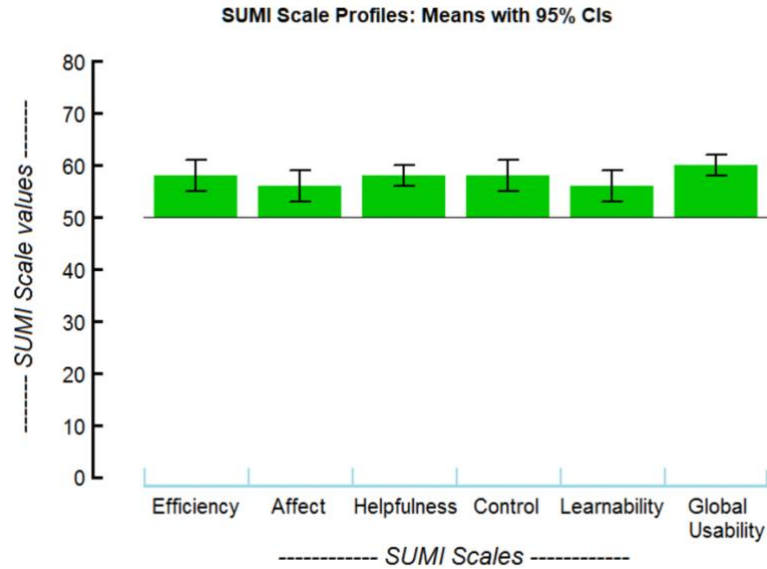


Figure 4: SUMI Scale Profiles: Means with 95% CIs

Figure 4 shows a bar graph displays the mean scores attained on various SUMI assessment subscales. The height of every bar corresponds to the average result for a particular subscale. The bar is shown in green whenever the average score surpasses 50, which serves as the benchmark. As shown in Table 2, our bars are all green because the results are all above 50. However, if the average score drops below 50, the bar will become red. The graph above issue also shows a range of results in which, if similar surveys were administered an infinite amount of time with the exact same number of participants, we could say with a high level of certainty (95%) that the true average score would reside. The graph's vertical "staples" serve as a representation of this. The importance of the SUMI score for that specific aspect depends on whether the 50 mark is present within or outside of this range, which affects our conclusions.

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

The proposed neural approach's usability assessment in Computer Assisted Translation (CAT) systems have been stated that 28 EMU students participated in the complete usability test survey, which was more than the advised minimum sample size. The SUMI scores with an average mean of 50 and a standard deviation of 10 presented in Table 5.1 of the results showed above-average user satisfaction. The created model's overall score of 60.43 (Table 5.2) confirmed the validity of hypothesis H6 and demonstrated an enhanced user experience. The Efficiency sub-scale had a score of 57.75, confirming hypothesis H2, while all other subscales received mean scores above 50, supporting hypotheses H3, H4, and H5. The distribution and average scores were shown visually using box plots and bar graphs, which consistently showed user satisfaction and the system's achievement of its goals. Particularly, an anomaly in the learnability sub-scale revealed that the expected normal distribution pattern may have deviated in some way. The outcome of the result therefore shows the empirical proof of the neural approach's efficiency in CAT systems and emphasize its potential to improve usability and user experience.

This research compared the usability evaluation of the neural technique in CAT systems with that of Machine Translation: A Study on Turkish-English Translation Assisted by Software from Eastern Mediterranean University Masters Thesis under the

supervisor of Asst. prof. Dr. Mustafa Tanel Babagil (Ismail et al, 2023). The current study focused on assessing the effectiveness of neural procedures, particularly in handling out-of-vocabulary (OOV) terms, in contrast to Ismail's research, which concentrated on a combination of translation methods to increase translation quality by using Rule Base Machine Translation and Statistical Machine Translation for testing the developed Hybrid Machine Translation Model, having a Global usability score of 56.41. The neural approach's efficiency in handling OOV terms was confirmed by the SUMI examination, which validated H6 with an overall score of 60.43. A realistic evaluation was helped by using SUMI. The processing of OOV words by CAT systems was successfully improved by sub-word tokenization, particularly Byte Pair Encoding (BPE). These findings provide developers with useful guidance for enhancing system performance.

The efficiency of neural techniques in CAT systems, particularly in handling uncommon or OOV terms, has been examined in this work. The research's conclusions show that sub word tokenization, in particular BPE, is a successful method for enhancing the capability of neural CAT systems to handle OOV terms. The neural model can successfully capture morphological variants and handle unseen words thanks to the application of BPE. The research has demonstrated that the neural model's effectiveness differs across different language pairs, which may be a result of the complexity of the target language or the caliber and amount of training data. Additionally, it was shown that the neural model outperformed current state-of-the-art CAT systems by employing the SUMI metric, a commonly used evaluation measure in the field of machine translation. These findings imply that the suggested method has the potential to considerably enhance how well CAT systems handle OOV words. It

can also be a useful tool for translators to increase the precision and effectiveness of their translations.

The results of this study have two benefits.

- a. It first sheds light on how well neural techniques work in CAT systems, particularly when processing OOV words.
- b. Second, it suggests that OOV words be handled by neural CAT systems using sub word tokenization, particularly BPE.

These conclusions have applications for CAT system development and can serve as a roadmap for developers to enhance the performance of their systems when processing OOV words.

6.2 Recommendations for Future Research

Further research for this paper may examine more sub word tokenization strategies and evaluate how well they handle OOV terms in neural CAT systems. The Unigram Language Model (ULM), which has demonstrated promise in various natural language processing tasks, is one potential strategy (Kudo & Richardson, 2018). Finding the best methodology for handling OOV words across several language pairs can be accomplished by contrasting the performance of ULM with that of BPE and other sub word tokenization techniques. Investigating the use of pre-trained language models for neural CAT systems is another area for future research. Pre-trained language models, like BERT, have demonstrated outstanding performance in a range of natural language processing tasks, including machine translation (Devlin et al., 2018; Radford et al., 2019). These models may be improved to handle OOV terms even better by testing them on language pairs. Investigating the impact of adding outside information

sources, like as ontologies or knowledge graphs, into neural CAT systems may also be worthwhile. By combining these knowledge sources, the system may be able to handle OOV words better and translate words more accurately. Finally, it is important to note that assessing machine translation systems is a never-ending challenge, with new metrics and evaluation techniques being created all the time (Graham et al., 2015). To better understand how neural CAT systems affect the translation process and user experience, future study may involve investigating alternative evaluation metrics and performing user research.

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APPENDICES

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

 <p>Doğu Akdeniz Üniversitesi "Erdem, Bilgi, Gelişim"</p>	<p>Eastern Mediterranean University "Virtue, Knowledge, Advancement"</p>	<p>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</p>
<p>Bilgisayar ve Teknoloji Yüksekokulu / School of Computing and Technology</p>		
<p>Zoom Out</p>		
<p>16.3.2023</p>		
<p><i>AWWAL OLAWOLE AJIDE is a student at the school of computing and technology, Eastern Mediterranean university and I guarantee that his usage of SUMI is solely for research purposes, and forms part of his 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 of SUMI is concerned, and that I will help the student to take reasonable steps to protect the intellectual property rights and copyright of SUMI.</i></p>		
<p><i>Mustafa Tanel Babagil Asst. Prof. Dr. in School of Computing and Technology (I.T)</i></p>		
 		
<p>www.emu.edu.tr</p>		

Appendix C: Permission to use SUMI

SUMI Permission for AWWAL O. AJIDE 🔗 1 🔍 📄

 **AWWAL O. AJIDE** 😊 ↶ ↷ ↸ ⋮
To: Mustafa T. Babagil; jzk@uxp.ie Fri 3/17/2023 11:46 AM

Dear Jurek Kirakowski

My name is Awwal Ajide, and I am a Master Student at Eastern Mediterranean University studying Information Technology. I am writing to request permission to use the SUMI tool for academic purposes in my research thesis.

My thesis topic is "Investigating the Effectiveness of Neural Approaches in Computer Assisted Translation (CAT) Systems." Specifically, I am exploring the use of neural machine translation (NMT) in improving the accuracy and efficiency of CAT systems. The goal of my research is to determine whether NMT-based CAT systems outperform traditional rule-based approaches and to identify the factors that contribute to their success.

I have recently filled the student application form and sent it, and my supervisor has sent a letter which has been scanned and sent over to your email, so as to enable me get an approval for SUMI tool. In order to evaluate the usability of the CAT systems, I would like to use the SUMI tool. I have reviewed the SUMI license agreement and privacy policy, and I understand the terms and conditions. I will ensure that any data collected through the tool will be kept confidential and will only be used for academic research purposes.

I kindly request your permission to use the SUMI tool for my research. I am confident that this tool will greatly benefit my research and provide valuable insights into the usability of the CAT systems.




Thank you for your consideration, and I look forward to your response.

Sincerely,

Awwal Ajide
21506028@emu.edu.tr

...

Appendix D: Approval from Ethics Committee

 <p>Doğu Akdeniz Üniversitesi "Erdem, Bilgi, Gelişim"</p>	<p>Eastern Mediterranean University "Virtue, Knowledge, Advancement"</p>	<p>Galileo Galilei Sk. / Str., 99628, Gazimağusa, KUZZEY KIBRIS / Famagusta, NORTH CYPRUS, via Mersin 10, TURKEY Tel: (+90) 392 630 1327 bayek@emu.edu.tr</p>
<p>Bilimsel Araştırma ve Yayın Etiği Kurulu (BAYEK) / Board of Scientific Research and Publication Ethics</p>		
<p>Reference No: ETK00-2023-0060</p>	<p>04.04.2023</p>	
<p>Subject: Your application for ethical approval.</p>		
<p>Re: Awwal Olawole Ajide and Asst. Prof. Dr. Mustafa Babagil</p>		
<p>Faculty of Engineering</p>		
<p>EMU's Scientific Research and Publication Ethics Board (BAYEK) has approved the decision of the Ethics Board of the Faculty of Engineering (date: 30.03.2023, issue: 23/1) granting Awwal Olawole Ajide and Asst. Prof. Dr. Mustafa Babagil from the School of Computing and Technology to pursue their work titled "Investigating the Effectiveness of Neural Approach in Computer Assisted Translation (CAT) Systems".</p>		
<p>Best Regards</p>		
		
<p>Prof. Dr. Yücel Vural Chair, Board of Scientific Research and Publication Ethics - EMU</p>		
		
<p>YV/ek.</p>		
<p>www.emu.edu.tr</p>		

Appendix E: Consent Form Participants

Awwal Olawole Ajide
MSc information Technology
05338627994
21506028@emu.edu.tr

CONSENT FORM

Dear Participant,

I am an MSc student conducting my thesis on the " INVESTIGATING THE EFFECTIVENESS OF NEURAL APPROACHES IN COMPUTER ASSISTED TRANSLATION (CAT) SYSTEMS".

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;

Awwal Olawole Ajide
MSc information Technology
Eastern Mediterranean University (EMU)
05338627994
21506028@emu.edu.tr

Asst.Prof.Dr. Mustafa Babagil
School of Computing and Technology,
Easter Mediterranean University (EMU)
0392-630-2885
mustafa.babagil@emu.edu.tr

Appendix F: Turnitin Originality Report

Computer Assisted Translation

ORIGINALITY REPORT

13%

SIMILARITY INDEX

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INTERNET SOURCES

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STUDENT PAPERS

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