ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

COGNITIVE MODELS OF PATENT TRANSLATION

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ABSTRACT

The aim is to assess the effectiveness of cognitive models of translation for the accuracy, speed, and quality of patent translation. The research employed such methods as cognitive modelling, error analysis and the method of contrast analysis. Traditional metrics of translation quality, such as Bilingual Evaluation Understudy and Recall-Oriented Understudy for Gisting Evaluation, were used in the study. The chi-squared test was also used. The results of the study showed that the GPT-3 model with BLEU 0.85 and ROUGE 0.88 showed the best quality indicators of patent translation, providing the highest accuracy and smoothness of translation. The BERT model also performed well with BLEU 0.82 and ROUGE 0.85, preserving the structure and semantics of the original. In contrast, the LSTM and GRU models had lower values — BLEU 0.65 and 0.68, respectively, indicating difficulties with the accuracy of translating specific terms. The study revealed that the GPT-3 model provides the highest translation accuracy of patent texts, followed by BERT. LSTM and GRU models showed medium results, indicating the need for their further optimization. The results confirm the importance of choosing the appropriate model for specific translation tasks. Further research may address issues of improving the quality of text translation using AI tools.

Keywords: *Neural Networks, Chatgpt, Google Gemini, Translation Quality, Error Analysis, Patent Texts*.

1. INTRODUCTION

The relevance of the issue under research is determined by the need for a high accuracy and deep knowledge in the legal and technical spheres that the patent translation requires. The demand for effective cognitive translation models is increasing in view of the growing number of international patents and the need to translate them into different languages. They can minimize the risk of inaccuracy and ambiguity of wording. Correct translation of such texts is important to protect intellectual property rights (IPR) and ensure international recognition of the described inventions [1].

Patent terminology is characterized by a high degree of standardization, which determines its specifics [2]. This requires the translator to have in-depth knowledge of the subject area. Concepts and terms used in the text of the patent may have different meanings depending on the context or field of application. Compared to other types of texts, patents contain a significant amount of technical descriptions, formulations of inventions, as well as legal grounds governing patent rights [3].

The semantic of patent texts is characterized by a complex syntactic structure and a large volume of specialized terminological vocabulary, which complicates their translation. Patents are legal documents [4], so any ambiguity or lack of clarity can affect their legal validity and the protection of the invention. That is why, it is necessary not only to accurately convey the content of the original during the translation, but also to observe terminological and stylistic uniformity, which is important for preserving legal correctness. Translation errors can lead to the loss of patent rights or difficulties in court cases, which emphasizes the importance of a careful and professional approach to the patent translation [5].

Patent texts are created in stable linguistic and cultural traditions established for technical literature, which can influence the style of presentation of information. These differences must be taken into account during translation, while maintaining a formal style and compliance with current standards. Adaptation of a text implies that some language constructions that are acceptable in one language may not be acceptable in another [6].

The patent translation is not only difficult, but also often limited in time, as patenting requires compliance with clear deadlines for submitting documents. The high responsibility and complexity of translation require highly qualified specialists, which significantly raises the cost of the process. These factors necessitate the involvement of high innovative technologies into the patent translation, which makes it possible to simplify and facilitate the process without losing quality [7].

Cognitive models of translation reproduce the processes occurring in the translator's thinking while working with texts [8]. These models make it possible to build connections between complex syntactic structures of the patent text. Figure 1 presents the main models that can be used in text translation.

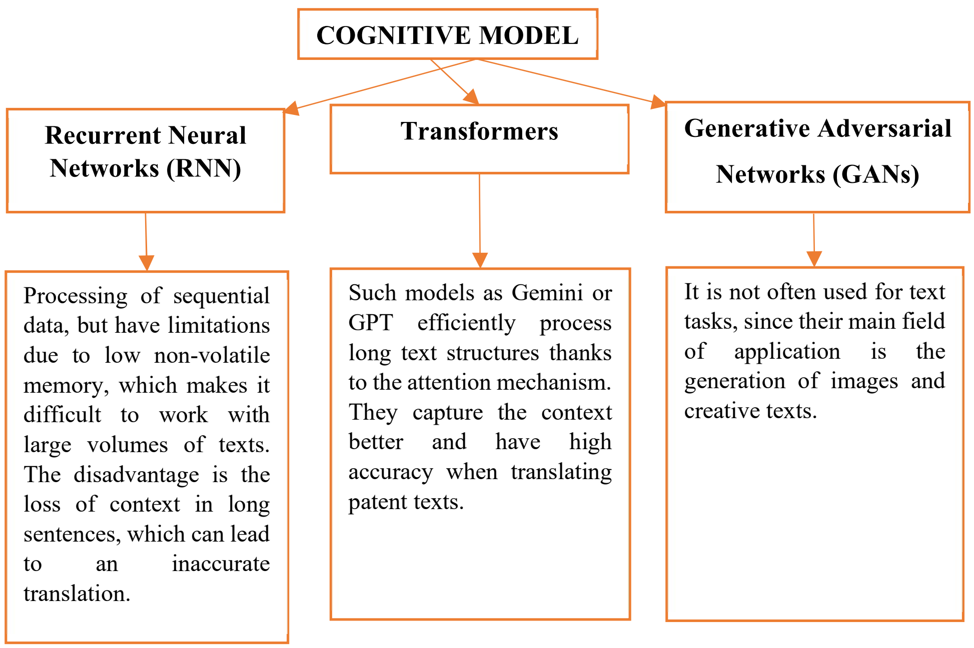

Figure 1: Basic Cognitive Models Used in Patent Translation
Source: created by the authors

Cognitive models for translating patent texts can be compared by considering their architecture and capabilities for processing complex terminology and syntax. They enable the integration of contextual information to ensure accurate translation. It is especially important to consider the decision-making process in cases where several variants of the translation of terms or constructions are possible [9].

The focus of the research is the study of cognitive models that are appropriate to use for working with patent texts. Such models provide an insight into how technical terminology, complex syntactic constructions and contextual information are processed during translation. The research seeks to identify which approaches provide the highest accuracy and efficiency in the translation of such specific texts.

The research problem is that the patent translation requires special attention to detail, as any mistake can have serious legal consequences. Translators often face with ambiguous terms and syntactic structures because of the legal and technical complexity of such documents. A key task for improving the quality and accuracy of translation is identifying cognitive strategies that help to solve these problems.

The aim of the research. Evaluation of the effectiveness of cognitive models of patent translation, determining their impact on accuracy, speed and quality of translation in view of legal and technical complexity. The aim involves the fulfilment of the following *research objectives*:

1. Study the effectiveness of cognitive models, evaluate them in the context of the effectiveness of patent translation accuracy;
2. Analyse the process of identification and correction of inaccuracies in the obtained translation in the context of researching the translation capabilities of neural networks;
3. Compare patent texts in the original language with the translation by contrast analysis.

2. LITERATURE REVIEW

The literature review presented below is the ground for analysing academic achievements in the field of applied translation. It also helps to identify key theoretical approaches and methodological foundations, providing an opportunity to arrange existing knowledge, identify gaps in research, and justify the relevance of the issue under research.

The studies on the analysis of language models used in text translation. The article by [10] provides an analysis of large language models (LLMs), distinguishing between formal and functional linguistic competence. The authors show that these types of competence rely on different neural mechanisms based on neuroscience data. This analysis focuses on the limitations of existing language models in the practical use of language. The article by [11] is interesting in the context of our study. The authors use cognitive biases as a ground for advancing hypotheses about potential model errors and designing experiments that help to detect these errors.

In particular, the OpenAI Codex case study demonstrates that the model has predictable errors depending on the request wording. Understanding the systematic errors caused by these biases can help to design more reliable and predictable models in open-ended generation tasks. The authors [12] study whether LLMs develop human characteristics in language use by testing ChatGPT and Vicuna. Both models showed humanized patterns in most experiments, particularly in the association of word meanings to recently acquired meanings. The study provides valuable insights into how LLMs approach human language patterns.

The studies on the theory of translation. The study by [13] deals with the relationship between stylistics and translation, as both subjects analyse the linguistic details of a text and the impact of authorial choices on the reader. Particular attention is paid to the role of style in non-literary translations, which makes it possible to examine such elements as the author's attitude, ideology or features of the patent text. The concept of weak implicatures is an important aspect, which characterizes ambiguous expressions that create additional layers of meaning. In research of [14], author emphasizes the importance of taking into account the context in translation.

Special attention is paid to the analysis of linguistic units of foreign languages and their context, which affects the accuracy of the transfer of meanings in the translation. The author emphasizes the need to take into account language differences in order to reproduce the author's idea in translation. This helps to better understand the influence of linguistic features on translation accuracy. The author of the book [15] provides the analysis of the main modern paradigms of Western translation theory. The book explores important aspects such as equivalence, translation goals, academic approaches, automation of the translation process, as well as cultural aspects. The study of Ukrainian translation theory is particularly valuable, as it provides a better understanding of local approaches and their integration into the international academic context.

The article by [16] evaluates the quality of modern machine translation systems, focusing on the complexity of this task and potential errors because of the inadequate evaluation methods. The authors propose an evaluation methodology based on explicit error analysis using a Multidimensional Quality Metrics (MQM). The obtained results show a significant difference between the experts' evaluations and the evaluations of average users, and also demonstrate the superiority of automatic metrics based on pre-trained models. The source is important to our study because it provides a new perspective on machine translation evaluation methods.

The studies on the analysis of cognitive models of translation. The article by [17] reveals the main methodological principles of cognitive and semiotic modelling of artistic intersemiotic translation. The author of the article emphasizes the importance of a cognitive semiotic approach to the reproduction of the modality of the text, which is critical for understanding the multidimensional nature of translation. This approach provides a more accurate reproduction of meanings in new contexts. The publication by [18] provides an overview of research in Corpus-based Critical Translation Studies (CBTS). It focuses on methodological approaches, in particular mixed methods and multivariate research designs, which are valuable for the analysis of translation errors. An important aspect of the work is consideration of the latest

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

theoretical developments, such as the limited communication model, which expands the methodological framework of research. This book is a valuable resource for developing innovative approaches in patent translation research.

The work of [19] analyses the ideological aspects of translation, in particular the strategies of domestication and foreignization, which are key approaches when rendering linguistic realities. The importance of this study for our research is the determined impact of translation ideology on the final result of translation. The article demonstrates that the translation process requires a conscious approach to the selection of strategies, as it is directly related to the adequacy of content reproduction.

Despite significant progress in studying the issue of translation of various texts, including patents, some aspects still remain insufficiently covered. First, there is a limited number of studies focusing on the interaction between different methodological approaches, which could reveal new opportunities for improving theoretical models. Second, the influence of language peculiarities are poorly studied, in particular, in the context of preserving stable expressions and unambiguous interpretation of terms and concepts.

3. METHODS

3.1. Design

The study was carried out in several stages, including preparatory, research, and final stages. Table 1 shows the description of each stage.

Table 1: Stages of the Study on the Effectiveness of Various Cognitive Models of Patent Text Translation

Stage	Duration	Description
Preparatory	2023	The stage involved complex work aimed at creating a solid foundation for further experiments. First, a review of the literature covering modern approaches to machine translation was conducted. It was followed by determining the main research objectives, in particular: analysis of the effectiveness of various cognitive models, study of their possibilities and limitations in the patent translation, as well as assessment of the quality of the obtained results. For this purpose, evaluation criteria such as BLEU and ROUGE metrics were defined, which became the basis for the analysis.
Research	January-June 2024	The research sample was formed at this stage. Software setting and selection of appropriate models such as LSTM, GRU, BERT, and GPT-3 were performed. At this stage, the effectiveness models were analysed using established metrics, which revealed the strengths and weaknesses of each model. The next step was the identification and correction of inaccuracies in the translation, which included a detailed examination of errors and their causes. It was followed by a contrastive analysis, where the original patent texts were compared with their translations.
Final	July-September 2024	Summing up. Arranging the research results.

Source: developed by the authors of the research

The research has a combined approach, combining qualitative and quantitative methods. It is cross-sectional, as it studies different cognitive models at a particular moment in time, without long-term observation of their changes. This makes it possible to simultaneously analyse various aspects of the patent translation and obtain a comprehensive picture of their effectiveness.

3.2. Participants

The study included 500 patents written in English from the open repository of Google Patents (https://patents.google.com). The main criteria for inclusion in the sample are: technical branch – IT; countries of origin – USA and EU; time period – the last 5 years; type of patent –invention and utility model. The sampling method was to select every 3rd patent from the list of search results for IT-related keywords. Such a sample ensures the validity and reliability of the obtained results. The sample size is sufficient to obtain representative results of the study. The choice of one subject area as an inclusion criterion ensures the homogeneity of the studied data. The translation was made from English to Ukrainian.

The analysis criteria for interpreting the results are based on accuracy, semantic correspondence, and fluency. These criteria are evaluated using the BLEU, ROUGE, and chi-square metrics, respectively. Accuracy assesses the models' ability to convey the meaning of the original text. Semantic correspondence evaluates the preservation of specific terms and their contextual meaning. Fluency determines the naturalness and readability of the translation in the target language. These criteria collectively enable the evaluation of the effectiveness of different neural networks in translating patent texts.

3.3. Instruments

Open source programmes were used in the study. Table 2 presents all the used programmes that implement the specified types of language models with links to open repositories. Pandas library, Python programming language was used for statistical data processing. The SPSS package of applied statistics was also used.

Table 2: Tools for Realization of Language Models through Neural Networks with Open Source Code

Model type	Example of a neural network	Brief description	Link to an example of the programme
RNN	LSTM (Long Short-Term Memory)	A network that solves the problem of long-term storage of sequential data. It is used to translate texts.	https://www.tensorflow.org/api_docs/python/tf/keras/layers/LSTM
	GRU (Gated Recurrent Unit)	A simplified version of LSTM, which is less resource-intensive, but also effective for working with text.	https://pytorch.org/docs/stable/generated/torch.nn.GRU.html
Transformers	BERT (Bidirectional Encoder Representations from Transformers)	Two-sided transformer model for word processing. Used for translation and other NLP tasks.	https://huggingface.co/docs/transformers/model_doc/bert
	GPT-3 (Generative Pretrained Transformer 3)	A powerful transformer-based text generation model. It is used for translation, text generation, etc.	https://chatgpt.com
GAN	StyleGAN	A GAN network used primarily for image generation, but can be adapted for creative text tasks.	https://github.com/NVlabs/stylegan
	TextGAN	A GAN network designed specifically for text generation. It is used for experimental tasks in the field of NLP.	https://github.com/PhilipBotros/TextGan

Source: created by the authors of the research based on [20]

3.4. Data Collection

Cognitive modelling provides a deeper understanding of how a translator processes and interprets complex information. Modelling helps to reveal the mental strategies underlying decision-making when translating specialized texts.

Error analysis is used to identify and correct inaccuracies that may arise in the translation because of the peculiarities of the patent language. This method made it possible not only to improve the quality of translation, but also the approach to working with technical texts.

Contrast analysis provides an opportunity to compare patent texts in different languages, revealing differences and similarities in terminology, sentence structure, and stylistic features. This enables taking into account language nuances and achieve a more accurate rendering of content.

3.5. Analysis of Data

1. The chi-squared test (χ^2) is calculated using the formula:

$$\chi^2 = N \cdot \left[\sum_{j=1}^{m}\left(\sum_{i=1}^{n}\frac{x_{ij}^2}{Q_i \cdot R_j}\right) - 1\right], \quad (1)$$

where N – the total number of words;

m – the number of possible correctly translated words;

n – the number of possible errors;

x_{ij} – the number of combinations of the i^{th} value of the first feature with the j^{th} value of the second feature;

Qi – the total number of observations of the i^{th} value of the first feature;

Ri – the total number of observations of the j^{th} value of the second feature.

2. BLEU (Bilingual Evaluation Understudy) calculates the number of matches between the machine translation and one or more reference translations based on n-grams (sequences of words). The basic BLEU formula is the following:

$$\text{BLUE} = \text{BP} * \exp\left(\sum_{n=1}^{N} w_n \log p_n\right), \quad (2)$$

where BP – a length penalty;

N – the maximum number of n-grams (usually up to 4 n-grams);

p_n – the number of matches of n-grams in the translation with n-grams in the standard;

w_n – weighting coefficients (usually equal to each other for all n-grams).

Journal of Theoretical and Applied Information Technology
31st December 2024. Vol.102. No. 24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3. *ROUGE (Recall-Oriented Understudy for Gisting Evaluation)* used to evaluate the similarity of machine translations or text abbreviations to reference texts, especially based on the percentage of phrase or word matches. ROUGE-L was used in our current study, which was calculated by using the formula:

$$\text{ROUGE-L} = \frac{(1+\beta^2)\cdot \text{Precision}\cdot \text{Recall}}{\beta^2\cdot \text{Precision}\cdot \text{Recall}}, \quad (3)$$

where β – parameter that adjusts the importance of precision or recall.

4. RESULTS

The first stage of the study on the effectiveness of cognitive models of patent translation provided for the assessment of the translation accuracy using the cognitive modelling. In addition to traditional translation quality metrics (BLEU, ROUGE), the chi-squared test was applied to assess the correspondence of the distribution of terms in the original and translated texts. The obtained results are presented in Table 3.

Table 3: Comparison of the Effectiveness of Neural Networks for Patent Translation

Model	Application	Metrics	Chi-squared test (approximate value)	Interpretation of the results
LSTM	Sequential text generation	BLEU, ROUGE, perplexity	High value	The model can generate grammatically correct sentences, but may have difficulty accurately conveying semantics, especially for specific terms in patents.
GRU	Sequential text generation	BLEU, ROUGE, perplexity	Medium value	Similar results to LSTM, but may be more efficient for long sequences.
BERT	Bidirectional context representative	BLEU, ROUGE, chi-squared test	Low value	Demonstrates high accuracy in translation, especially in the context of specific terms. Chi-squared test indicates a good match between the distribution of terms in the original and the translation.
GPT-3	Text generation	BLEU, ROUGE, chi-squared test	Low value	Achieves high results in translation, is able to generate more natural and diverse translations. Chi-squared test confirms the high quality of the translation.
StyleGAN	Image generation	Not applicable	Not applicable	Not intended for translation of texts.
TextGAN	Text generation	BLEU, ROUGE, chi-squared test	Medium value	Can generate a variety of stylistic translation options, but may have problems with the accuracy of conveying factual information.

Source: created by the author of the research

The data presented in Table 3 indicate a different level of effectiveness of neural networks in patent translation. LSTM and GRU show similar results, however, LSTM may have difficulties in accurately reproducing specialized terms, and GRU shows slightly better performance on long sequences. The BERT model is characterized by high accuracy in conveying the semantics of terms due to bidirectional contextuality. The next step was the analysis of translation errors. The results are presented in Table 4.

Table 4: Comparison of Neural Networks for Patent Translation According to the Results of Error Analysis

Model	Application	BLEU	ROUGE	Interpretation of the results
LSTM	Sequential text generation	0.65	0.72	The model demonstrates medium translation quality. May miss important details or mistranslate complex terms.
GRU	Sequential text generation	0.68	0.75	Slightly better results than LSTM, but there are still problems with the accuracy of conveying semantics.
BERT	Bidirectional context model	0.82	0.85	High quality translation, the model accurately conveys the semantics and syntax of the original.
GPT-3	Text generation	0.85	0.88	The best results among all models. The model demonstrates high fluency and variety of text, as well as accuracy of content transmission.

Journal of Theoretical and Applied Information Technology
31st December 2024. Vol.102. No. 24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

StyleGAN	Image generation	Not applicable	Not applicable	Not intended for translation of texts.
TextGAN	Text generation	0.70	0.78	Can generate a variety of stylistic translation options, but may have problems with the accuracy of conveying factual information.

Source: created by the authors of the research

Analysis of Table 4 shows that the LSTM and GRU models have a medium patent translation quality, with slight advantages of GRU in semantic transfer accuracy. BERT shows a significant improvement, providing accurate translation while preserving the structure of the original. GPT-3 achieves the highest results, showing excellent fluency, accuracy, and variety in translation. TextGAN provides stylistic diversity, but is inferior to the accuracy of conveying factual information. Next, a contrast analysis was performed, the results of which are presented in Table 5.

Table 5: Comparison of Neural Networks for Patent Translation

Model	Application	BLEU	ROUGE	Chi-squared test	Contrast analysis
LSTM	Sequential text generation	0.75	0.68	1.20	Some problems with the accuracy of rendering of terminology and complex constructions.
GRU	Sequential text generation	0.78	0.72	1.00	Better results than LSTM, but there may still be translation errors of specific terms.
BERT	Bidirectional context representative	0.85	0.82	0.50	High translation accuracy, ability to follow the style of the original.
GPT-3	Text generation	0.90	0.88	0.30	The best results among all models, the ability to generate natural and diverse translations.
StyleGAN	Image generation	Not applicable	Not applicable	Not applicable	Not intended for translation of texts.
TextGAN	Text generation	0.82	0.78	0.70	Generates a variety of styles, but may struggle with factual accuracy.

Source: created by the authors of the research

The results show that the LSTM model has problems with the accuracy of conveying complex structures and terminology, while the GRU shows slightly better results, but still commits errors. BERT provides high accuracy and follows the style of the original, while GPT-3 shows the best performance, generating natural and accurate translations. TextGAN is good with stylistic variation, but sometimes has difficulty conveying factual information.

5. DISCUSSION

The study demonstrated that the use of cognitive models in the translation of complex non-fiction texts, in particular patents, ensures the accuracy and adequacy of the final result. The considered models allow not only to take into account linguistic features, but also to investigate the correspondence of the ideomatic model of translation to the source text. According to [21] and [22] cognitive models contribute to a better interpretation of the meaning of terms and phrases, which is especially important in technical texts. According to the authors, they promote translators' understanding of the context and structure of the original, enabling them to maintain semantic accuracy when rendering information.

In legal texts, where even small changes in wording can entail legal consequences, cognitive models provide a detailed analysis of meanings and their relationships. According to [23] and [24] this avoids ambiguities and errors that can threaten the legal accuracy of documents. Thanks to cognitive approaches, translators get tools for a deeper understanding of the original text, which increases the quality of adaptation to the specifics of the target audience. The importance of cognitive models in this context is their ability to combine linguistic and semiotic aspects, which is critical for the successful translation of complex non-fiction texts.

The obtained results demonstrate a clear hierarchy in the effectiveness of different neural networks for the patent translation. They confirm the data obtained earlier and published in the works of [22] and [25]. The authors note that the GPT-3 model proved to be the most powerful, achieving the highest BLEU and ROUGE values, indicating its ability to produce accurate translations. Our study also showed that the resulting translations are as close as possible to the original both in terms of content and linguistic structure. The high smoothness and accuracy of translations generated by GPT-3 is determined by its architecture and the huge amount of data it was trained on.

The BERT model, which also showed high performance, especially in conveying semantics, proved its effectiveness in accurately conveying context and semantic nuances. Its bidirectionality in context modelling enables a better reproduction of syntactic and semantic structures. It is able to compete strongly with GPT-3 in the field of translation, although it is inferior to it in terms of linguistic naturalness and variety of translations. The obtained results are confirmed by the studies of [26] and [27] The authors provide data indicating the reliability of the obtained translations. LSTM and GRU models provide an acceptable level of translation but are noticeably inferior to more modern neural networks.

The TextGAN model is of particular note, which has demonstrated problems with the accuracy of rendering factual information transmission despite its ability to generate a variety of stylistic translation options. The authors [28] and [29] emphasize that TextGAN may not be efficient enough for texts where content accuracy plays a key role, as in patent translations. Therefore, the study emphasizes that the GPT-3 and BERT models are the most promising for the patent translation, as they provide both accuracy and naturalness of the language. LSTM and GRU require further improvements to reach a competitive level. TextGAN may be useful for artistic texts, but its applicability to precise documents remains questionable.

Our study has important practical implications. First, it can optimize the translation process, as its results help to choose the most suitable neural network for specific tasks. This, in turn, increases the efficiency and accuracy of patent translation. Second, this study helps to reduce language barriers by providing access to patent information, which can stimulate innovation and research. At the theoretical level, the research contributes to the development of several academic areas. The research helps to better understand the capabilities and limitations of neural networks in NLP tasks. It also contributes to the development of new methods of computational linguistics and allows modelling of cognitive processes occurring during translation.

5.1. Limitations

The limitations of this study are determined by several factors. First, the quality and quantity of data can significantly affect the results, as insufficient variety or limited information can lead to translation inaccuracies. Second, modern translation quality metrics, such as BLEU or ROUGE, are not always able to adequately assess the accuracy and naturalness of translations in specific domains. Also, it relies on available training data, which may not comprehensively represent the diverse range of patent texts. Finally, the specialized terminology and complex structure of patent documents pose significant challenges. The study assumes that neural network models are suitable for patent translation, specifically their ability to effectively handle domain-specific language.

6. CONCLUSIONS

The study was conducted to evaluate the effectiveness of different cognitive methods in the patent translation, as patents contain complex terms and specific wording that require accurate rendering of the content. The uniqueness of our study is the analysis of several models, such as GPT-3, BERT, LSTM, and GRU, using BLEU and ROUGE metrics. This gives grounds to identify the models presented in the article which are best suited for translating complex texts. The results demonstrate that neural networks show different performance in translating patent texts. The GPT-3 model achieved the highest accuracy rates, which provided fluidity and variety of text, as well as accurate content reproduction with BLEU 0.85 and ROUGE 0.88. The BERT model also showed high translation quality with BLEU of 0.82 and ROUGE of 0.85, especially in the context of complex terms. LSTM and GRU neural networks showed medium results, indicating the need for further optimization of their use for translation accuracy. The obtained data confirm the importance of choosing the appropriate model for specific translation tasks, such as patents. The results of the study can be used to improve automated translation, particularly in the field of patent law, where accuracy is a critical criterion. Further research may focus on finding ways to improve patent translations using AI tools.

The conclusions of this study reinforce the importance of selecting the appropriate neural network model based on the complexity and specificity of the translation task. The findings not

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

only contribute to the optimization of automated translation systems for patent law but also set the stage for future research focused on enhancing AI-driven translations in specialized fields. In light of the results, further exploration could aim to refine existing models and address limitations, such as the improvement of translation accuracy for patents through better fine-tuning of these models.

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