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Abstract: The relevance of the topic lies in the fact that, to create a machine translation program from English to Uzbek based on new mathematical models constructed on an expandable input language and through the morphological analysis of noun-tonoun derivational affixes in the noun word class, it is first necessary to study the degree of correspondence of affixes across word classes in both languages. This article presents a detailed theoretical discussion with examples on this issue. Thoughts are expressed on creating high-quality computer translation from English into Uzbek, which belongs to the Turkic language family as an agglutinative language that has not been sufficiently studied. Based on new mathematical models, the correspondence percentages between roots and affixes are provided. When affixes do not match, the translation of the input word's affix into the output word is addressed according to mathematical models developed for achieving semantically correct translation. The article also provides directions for addressing existing problems and resolving semantic inaccuracies. Furthermore, the necessity of constructing new mathematical models for both languages is considered, taking into account the rich morphology and affixation of Uzbek, as well as the rule of dividing morphemes for translating words belonging to each word class into another natural language. The work is aimed at eliminating meaninglessness and abstractness in translating scientific texts from Uzbek into English. Proposals are put forward for creating a computer translation program based on new mathematical models. Additionally, the article explores the feasibility of accurately capturing grammatical differences between the two languages through a mathematical model comprising morphological, syntactic, and semantic transfer stages. Moreover, considering the rich morphology and affixation of Uzbek and the morpheme division rule for translating words belonging to each word class, an experiment, the architecture, components, and implementation stages of a new rule-based mathematical model were used in the automatic translation process between Uzbek and English.

Keywords: Machine Translation, Natural Language, Expandable Input Language, Input Text, Output Text, Computer Translation, English Language, Uzbek Language, Noun Word Class, Noun-Forming Affixes from Nouns, Mathematical Model, New Mathematical Models of Words, Weight, Young Researchers (By Fields of Specialization), University Teachers (PPS).

Manuscript received on 01 September 2025 | Revised Manuscript received on 12 September 2025 | Manuscript Accepted on 15 September 2025 | Manuscript published on 30 September 2025.

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Ministries and Agencies, Higher Education Institutions (HEIs), Clusters, Industry Employers, International Organisations.

Abbreviations:

NL: Natural Language
MT: Machine Translation
MM: Mathematical Models
HEIs: Higher Education Institutions

I. INTRODUCTION

At the current stage of translation activity, the use of innovative technologies has particular importance. These primarily include information technologies. Machine translation can be defined as a field of artificial intelligence that enables the automatic conversion of natural languages from one into another. To date, the direction of translation from Uzbek into English and vice versa has not yet been fully systematized. Therefore, it is considered essential to develop new mathematical models based on an expandable input language for natural language processing, and to build a system that relies on morphological and syntactic knowledge. Given the rich affixation system of the Uzbek language, its translation should be approached not through traditional statistical models, but rather through a rule-based methodology. Only if we can teach a computing machine the mechanisms of the human brain will it become possible to create modern, high-quality machine translation systems based on scientific terminology by managing advanced systems. Every natural language (NL) is a complex system consisting of components that are not mathematically structured or formally defined. However, through natural language processing, it is possible to identify the unstructured elements within an NL and formalize them using a linear methodology—this includes determining word structure, constructing logical-linguistic models for parts of speech and sentence types, and creating mathematical models through a special meta-language. This methodology is referred to as the level of formalization of a language. The level of formalisation, in turn, defines the degree of semantic formalisation in the NL and the accuracy of the algorithm. A superficial understanding of the level of formalization treating a formalized language as an abstract structure detached from meaning and reduced to a simple logical framework-leads to the low efficiency of machine translation. Formalization makes it possible to divide a

language into different components, analyze their interrelations, and describe its semantic structure. The

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founders of machine translation were representatives of the fields of cybernetics and mathematics, and later, linguists began to participate in this work actively. Thus, the ideas of machine translation gained great importance in the development of theoretical and applied linguistics throughout the world. In parallel with this direction, the theory of formal grammar was created, and attention was paid to the creation of a model of language and its separate entities. At the current stage of translation activity, the problem of using innovative technologies is of particular importance. These mainly include information technologies. Only if we can teach the working mechanisms of the human brain to a computer will we be able to create modern quality machine translation based on scientific terms by controlling modern systems [1]. Yu. N. Marchuk, a Russian scientist, emphasised the necessity of using human resources to reflect the static description of the language and the dynamic translation process in solving the current problems of translation modelling and scientific and technical information. English stands out as one of the most commonly spoken languages worldwide. For individuals who are not native English speakers, the investment required to learn a new language is substantial, and attaining fluent communication demands challenges [2]. In formal settings and situations where extensive information exchange is necessary, relying solely on human translation is no longer sufficient to meet the increasing demand [3]. During the communication, lengthy English sentences are conventional [4]. However, the grammatical structure of English differs from that of other languages. When machine translation algorithms translate extended English sentences using a direct one-to-one mapping approach, it often results in grammatically incorrect translations and, in severe cases, translation errors [5]. Choi et al. Contextualized word embedding vectors using a nonlinear bag-of-words representation of the source sentence. Experimental results showed significant improvements in translation quality using their proposed contextualization and symbolization methods. This study outlines the fundamental framework of intelligent machine translation algorithms and optimizes LSTM-based intelligent machine translation algorithms by incorporating a long sentence segmentation module and a reordering module. Utilizing mathematical models in con - temporary highquality machine translation emphasizes the concept of employing them within translation processes. If the computer can be programmed to understand this mathematical model in a language that it comprehends, then it is possible to achieve appropriate translation into the target language. At present, machine translation is advancing in providing us with useful translations in many languages and various fields. Suppose machine translation is used in scientific fields, for example. In that case, one of the inevitable issues is encountering ambiguous words and content that loses its original meaning, despite some improvements in recent years. The research that we have conducted has made significant progress in achieving more meaningful machine translation by addressing some of these issues. However, it is essential to admit the challenges that have not been sufficiently resolved in machine translation. The foundation of machine translation is considered computer linguistics, but every natural language (NL) is a complex system composed of mathematically unstructured and unformulated components. In accordance

with the scientific work by Y.N. Marchuk [6], various concepts of machine translation models, as developed by mathematicians and linguists, are illustrated in detail. He also describes one of the machine translation models based on translation writing. According to the findings of this article, users often resort to MT only when necessary, since its output is frequently of insufficient quality. For these users, the author suggested the need to develop MT systems that ensure high-quality translation [7]. Unlike other Turkic languages, Uzbek is considered a low-resource language with a highly agglutinative structure. A single word can represent an entire sentence. For Uzbek, well-developed rule-based MT resources are lacking [8]. For example, some studies on sentiment analysis have been conducted. Despite various challenges, the Uzbek language must actively participate in the information society in the era of globalization [9]. Several works can be cited here that deal with morphological analysis and root word identification in Uzbek [10]. However, articles dedicated to the formalization of natural languages are minimal. At the same time, there are sufficient studies devoted to various aspects of Turkic languages. For example, [11] conducted sentiment analysis in Kazakh and Russian, including the emotional analysis of Kazakh sentences based on ontology. The mathematical model of the Russian language is presented in [12], where functions representing specific words are considered as part of the mathematical framework. This approach requires the creation of numerous functions for a computer translator and is complex from the perspective of practical application.

II. METHODS

Currently, machine translation (MT) plays a crucial role in the modern world. It is widely applied not only in the translation of scientific, literary, or official-legal texts but also in everyday use within multilingual environments. Despite the significant progress achieved over the past 20 years, existing MT systems still face persistent challenges, such as the lack of contextual understanding, incorrect use of expressions, grammatical errors, and issues with translation quality.

Automatic translation systems (Google Translate, Microsoft Translator, DeepL Translator, Yandex Translate, Amazon Translate) for English–Uzbek and Uzbek–English demonstrate several shortcomings:

Since Uzbek belongs to the group of agglutinative languages, word formation and the semantic structure of sentences depend heavily on affixes in each word.

This structural difference between English and Uzbek has not been resolved in the aforementioned automatic translation systems.

No specific instrument has been developed to formalize natural languages to address this issue.

For accurate translation between languages, including English and Uzbek, natural languages have not been sufficiently formalized, nor have their various models been developed.

To overcome the shortcomings mentioned above, Professor M.Kh. Khakimov of the National



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University of Uzbekistan developed a special expandable input language aimed at the formalization of natural languages. As a result of the creation of this expandable input language, linguistic and mathematical models have been developed for parts of speech and sentence types in English, Russian, and Uzbek.

In natural language (NL) processing, grammatical analysis involves several stages. It is advisable that all mathematical frameworks related to morphology and syntax, including the construction of mathematical models of parts of speech, should be developed so that all normative cases of the language are covered during computer word analysis. Taking into account word-forming affixes in English and Uzbek statistically, and creating their semantic databases, helps to design software more precisely. For machine translation, isolating affixes into separate databases and defining their models is crucial in the analysis process. Any part of the NL processing workflow may change in the future, which imposes specific requirements on the development of software environments for multilingual machine translation. Uzbek belongs to the agglutinative group of languages, while English is classified as an analytic language. Therefore, fundamental grammatical contradictions can be observed. In machine translation, morphological analysis is essential for segmenting word components and identifying grammatical rules of the studied language. Since Uzbek is an agglutinative language, the analysis of roots and affixes is closely linked to lexical-semantic, phonetic, and grammatical phenomena [13]. Words belonging to the independent parts of speech in Uzbek are formed by (1) affixation and (2) composition. Taking these aspects into account, in this study, we propose new mathematical models for the English-Uzbek translation system, designed for a rule-based MT program and constructed based on an expandable input language. The proposed model automates grammatical analysis of language units, categorization into parts of speech, and translation based on syntactic compatibility. Structurally, the system is grounded in mathematical models, where each model performs functional analysis of roots and affixes as the basis for translation.

In machine translation, it is crucial to construct new mathematical models of each word through morphological analysis of natural languages. This is particularly important in agglutinative languages such as Uzbek, where words are composed of multiple affixes. When translating such words into another natural language, it is essential first to identify the specific type of affix attached to the root and then provide an equivalent in the target language. For this purpose, the construction of new mathematical models of roots and affixes, along with the assignment of weight coefficients, plays a key role in ensuring accurate translation.

In this paper, we examine the derivational affixation process of nouns in Uzbek and propose new mathematical models for translating scientific texts from Uzbek into English by segmenting words into morphemes. We demonstrate the significance of these models and weight coefficients for roots and affixes in developing a machine translation system. The importance of this approach is illustrated through the percentage of correspondence and non-correspondence of affixes between the two languages.

The main goal of this work is to address the problem of vague and meaningless translations that arise in the process of translating scientific texts from Uzbek into English. We can confidently state that large language models, although designed for more than one hundred languages, often generate semantic inconsistencies when applied to Uzbek–English scientific translation. This means that researchers who attempt to translate scientific texts from another natural language into Uzbek are likely to obtain content with distorted meaning.

To address these challenges, Professor M.Kh. Khakimov of the National University of Uzbekistan developed an expandable input language [13], which enables the processing of arbitrary natural languages. The primary objective of this study is to design a high-quality translation system for scientific articles from English into Uzbek and vice versa. To achieve this, we propose analyzing parts of speech in both languages using morphological analysis, segmenting each word into morphemes, and distinguishing roots from their affixes.

In our previous research, we developed new mathematical models for the structure of nouns using the expandable input language. In this paper, we also construct new mathematical models for affixes in both languages based on the expandable input language, and analyze their correspondences and mismatches using the data presented in Table 1.

The process of creating mathematical models based on the expandable input language includes the following tasks [14]:

- Dividing words into morphemes;
- Determining the grammatical function of each morpheme;
- Finding the translation correspondence of each morpheme;
- Generating contextual transformation and translation;
- Expression in mathematical and algorithmic form.
- We can define the weight of word classes in any natural language as follows:
- Words belonging to the noun word class (C) 0.85;
- Words belonging to the adjective word class (P) 0.6;
- Words belonging to the verb word class (G) 0.9;
- Words belonging to the adverb word class (N) 0.4;
- Words belonging to the pronoun word class (M) –
 0.5.
- Words belonging to the numeral word class (F) 0.5;
- Conjunctions (Y) 0.2
- Prepositions (D) -0.4
- Non-independent word classes (i.e., auxiliary word classes) other word classes (U, D, Y, L) – 0.07.
- Based on this, the numbering of word types helps in calculating the weight of two languages.
- The meaning of symbols in the tables presented below in this article:

■ ⊕ — addition operation;



- — operation of "connection" or "non-connection"
 of the next component;
- \$ selection operation;
- syntax $\{(i), (1/h) \}$ [3].

The following notations were adopted to make the tables more concise. All notations in the text are constructed based on: V2 — word weight; V3 — affix weight; (MM) — mathematical model; C — designation of the noun as an independent part of speech; C(A) — noun-forming affix; D — preposition; M10(C) — possessive pronoun as a noun; C(D4) — definite article; X — variables; X2 — possessive affix; X3 — case affix; O'ZTOTOTYA — Uzbek noun-deriving affixes; ITMA — corresponding English affixes; ITBMF — percentage of correspondence between affixes in the two languages.

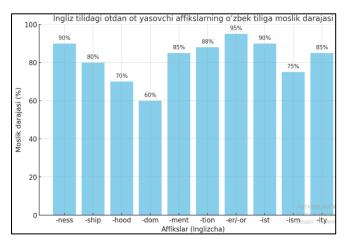
III. RESULTS

For the comparative analysis of 22 English noun-deriving affixes with their Uzbek counterparts, the mathematical model (MM) of each Uzbek affix and the affix weight (V3) were first constructed. This step is essential, as in machine translation, it is crucial to design the translation system based on precise mathematical models developed through syntactic, semantic, and morphological analyses of both languages. Therefore, the English noun-deriving affixes $f_{[i,1-n]}C(A_{[i]})$ and the affixes related to the noun category (C) were initially modelled mathematically by separating roots and affixes. The weight coefficients of each affix were then determined for both languages.

Table I: English Noun-Deriving Affixes, Their Corresponding Uzbek Affixes, and New Mathematical Models with Weight Coefficients

ITMYMEA	(MM) va V3	O'ZTOTOTYA	(MM) va V3
-er	$_{[i,1-h]}C(A_{[i]}) 0.850101$	-chi	$_{[i,1-h]}$ C(A _[i]) 0.850101
mate	$f_{[i1,1-h]}C(A_{[i1]}) 0.850102$	-dosh	$f_{[i1,1-h]}C(A_{[i1]}) 0.850102$
-er	$f_{[i2,1-h]}C(A_{[i2]}) 0.850101$	-bon	$_{[i2,1-h]}C(A_{[i2]}) 0.850103$
-er	$f_{[i3,1-h]}C(A_{[i3]}) 0.850101$	-ham	$f_{[i3,l-h]}C(A_{[i3]}) 0.850104$
-er	$_{[i4,1-h]}$ C(A _[i4]) 0.850101	-xon	$f_{[i4,l-h]}C(A_{[i4]}) 0.850105$
-ist	$f_{[i5,1-h]} C(A_{[i5]}) 0.850103$	-parast	$f_{[i5,l-h]}C(A_{[i5]}) 0.850106$
-league	$f_{[i6,1-h]} C(A_{[i6]}) 0.850104$	-go'y	$f_{[i6,l-h]}C(A_{[i6]}) 0.850107$
-or	$f_{[i7,1-h]} C(A_{[i7]}) 0.850105$	-vachcha	$f_{[i7,l-h]}C(A_{[i7]}) 0.850108$
-er	$f_{[i8,1-h]} C(A_{[i8]}) 0.850106$	-boz	$f_{[i8,l-h]}C(A_{[i8]}) 0.850109$
-er	$_{[i9,1-h]}$ C(A _[i9]) 0.850101	-iy	$f_{[i9,1-h]}C(A_{[i9]}) 0.850110$
-er	$f_{[i10,1-h]}C(A_{[i10]}) 0.850101$	-navis	$f_{[i10,1-h]}C(A_{[i10]}) 0.850111$
-er	$f_{[i11,1-h]}C(A_{[i11]}) 0.850101$	-gar	$_{[i11,1-h]}C(A_{[i11]}) 0.850112$
-er	$f_{[i12,1-h]}C(A_{[i12]}) 0.850101$	-kor	$f_{[i12,1-h]}C(A_{[i12]}) 0.850113$
-	$f_{i13,1-h}C(A_{i13})$	-furush	$_{[i13,1-h]}C(A_{[i13]}) 0.850114$
-ist	$f_{[i14,1-h]}C(A_{[i14]}) 0.850103$	-shunos	$_{[i14,1-h]}C(A_{[i14]}) 0.850115$
-er	$f_{[i15,1-h]}C(A_{[i15]}) 0.850101$	-xo'r	$f_{[i15,1-h]}C(A_{[i15]}) 0.850116$
-	$_{[i16,1-h]}C(A_{[i16]})$	-paz	$_{[i16,1-h]}C(A_{[i16]}) 0.850117$
-er	$f_{[i17,1-h]}C(A_{[i17]}) 0.850101$	-dor	$\frac{s_{[i17,1-h]}C(A_{[i17]})}{0.850118}$
-er	$f_{[i18,1-h]}C(A_{[i18]}) 0.850101$	-soz	$f_{[i18,1-h]}C(A_{[i18]}) 0.850119$
-er	$_{[i19,1-h]}C(A_{[i19]}) 0.850101$	-do'z	$_{[i19,1-h]}C(A_{[i19]}) 0.850120$
-er	$f_{[i20,1-h]}C(A_{[i20]}) 0.850101$	-kash	$f_{[i20,1-h]}C(A_{[i20]}) 0.850121$
-	$_{[i21,1-h]}C(A_{i211})$	-bin	$_{[i21,1-h]}C(A_{i21]}) 0.850122$

In Table 1 above, we analyzed the degree of correspondence of the 22 English noun-deriving affixes $\{i_i,1-22\}$ $C(A_{[i]})$ to their Uzbek equivalents, and the percentage of correspondence is illustrated in Figure 1 below in the form of a diagram.



[Fig.1: Diagram of the Correspondence of English Noun
- Deriving Affixes to Uzbek Affixes]

The analysis is presented in the figure.1 clearly illustrates the morphological relationships between English and Uzbek. Out of the 11 English affixes, five correspond to Uzbek affixes with a high percentage of similarity. Three of the 11 affixes have no equivalents in the Uzbek language. Six affixes show an average level of correspondence to Uzbek, while the remaining eight affixes correspond to English at a very low level. These percentage values are reflected in the diagram shown in Figure 1.



[Fig.2: The Translation of the Corresponding English Affix <chi> when Attached to the Root into Uzbek]

In Figure 2 above, when the Uzbek root $f_{[i,1-h]}C$ is combined with the nounderiving affix $f_{[i,1-22]}CA_{[i]}$, the

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new word ishchi ("worker") is formed. The translation of this newly formed Uzbek word ishchi into English, based on the latest mathematical model, was achieved with 100% accuracy. This is because the word ishchi in Uzbek is derived in the same way as in English, where work+er is formed by attaching a highly corresponding affix to the root. If the grammatical and morphological structures of the two languages fully matched in creating a machine translation system, the translations in EVX and EVIX texts would reach up to 98% accuracy. However, the natural languages selected for this study belong to two different language families. Therefore, in developing a machine translation program from Uzbek into English or vice versa, we encounter inevitable challenges, which can only be resolved through the construction of new mathematical models.

Let us now consider the second noun-deriving affix \$[i,1] $_{22}$ C(A_[i]) with the example of the word *gapfurush*. In this word, the root $f_{i,1-h}C$ and the affix $f_{i,1-22}C(A_{i,1,2})$ combine to form a new word. When translated into English using the latest mathematical model, the result shows that a single word may be generated from the combination of two elements. In the first example above, the Uzbek affix -chi corresponds entirely to the English affix -er, ensuring 100% translation accuracy. However, the Uzbek affix -furush has no equivalent in English. Therefore, words such as *gapfurush* or *lattafurush* must be translated into English by relying on their meaning and rendering them as compound expressions. From these examples and results, it can be concluded that the newly developed mathematical models make it possible to represent non-corresponding affixes between the two languages through compound constructions. This, in turn, creates the potential for building a high-quality machine translation system.



[Fig.3: The Latest Mathematical Model]

In Table 1 above, two out of the 22 Uzbek noun-deriving affixes $f_{i,1-22}C(A_{i})$ are presented as examples. The affix chi, which shows the highest level of correspondence, forms a new noun in Uzbek through the combination of a root and an affix, and its English equivalent was translated accurately using the latest mathematical model. By contrast, the affix furush has no direct equivalent in English. Therefore, the appropriate English translation, based on the latest mathematical model, is illustrated in Figure 3. For the remaining 20 affixes, similar analyses were carried out and new mathematical models were constructed. As shown in Table 2 below, 19 of the 22 Uzbek noun-deriving affixes \$[i,1-_{22]}C(A_[i]) correspond to English affixes with varying percentages of equivalence. The other three affixes do not exist in English and therefore have no direct translation; as a result, they are marked as non-equivalent.

Table II: The Percentage of Correspondence of Uzbek **Noun-Deriving Affixes to English**

English Equivalent Affix(es)	Uzbek Affix	Match %
-er, -or, -ist	-chi	98%
-mate	-dosh	95%
-er	-gar	65%
-er	-kor	70%
-keeper, -tender	-bon	90%
-holder, -owner	-dor	70%
-ist, -ologist	-shunos	92%
-lover, -fan	-boz	50%
-	-furush	0%
-eater	-xoʻr	45%
-	-paz	0%
-maker, -builder	-soz	68%
-sewer, -stitcher	-doʻz	75%
-carrier	-kash	65%
-singer, -reciter	-xon	65%
-ist, -worshipper	-parast	55%
-ling, -let	-vachcha	20%
-teller, -speaker	-goʻy	60%
-ic, -al, -ous	-iy	85%
co-, -mate	-ham	70%
-writer	-navis	80%
-	-bin	0%

The structural sequence of compound words in Uzbek, along with their mathematical models (MM) and weight coefficients (V2), is presented in Table 3.

Table-III: Construction of New Mathematical Models for Compound Words in Uzbek

Of The Base (MM)	Of The Affix (MM) and Weight	The (MM) and the Weight of X	The (MM) and the Weight of X2	The (MM) and the Weight of X3
$_{[i1,1-10]}$ C	$_{[i1,1-10]}^{S}C(A_{[i]}) \ 0.850101$	⊕↓ X 0101	${}^{\$_{[i1,1-10]}}X2_{[i1]} \ 030n$	\$ _[i1,1-5] X3 _[i1] 020n

Based on the notations given in Table 3 above, the mathematical model (MM) of a compound noun can be represented in its general form.

$$\S_{[i,1-h]}C_{[i]} \bigoplus \downarrow \S_{[j,1-22]}C(A_{[j]}) \bigoplus \downarrow X \bigoplus \downarrow \S_{[i1,1-10]}X2_{[i1]} \bigoplus \downarrow \S_{[i1,1-5]}X3_{[i1]}$$
 (1)

The general mathematical model (MM) shown in (1) can also be constructed for the remaining 22 noun-deriving affixes \$[i,1-22]C(A[i]). For compound words, the (MM)

primarily changes in terms of roots and affixes, while the elements X, X2, and X3 may or may not appear in the EVX text. In Table 3 below, the mathematical models (MM) and weight coefficients of the 22 noun-deriving affixes \$[i,1-

22]C(A[i]) presented above are given. Using the general form of the (MM) in (1), we now construct new



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mathematical models (MM) for the formation of compound words in Uzbek and English by applying each root and affix. As an example, let us consider the Uzbek word <ishchilarimizdan> ("from workers"). our Through morphological analysis, the word is segmented into the following morphemes, and a new mathematical model (MM) is developed for each morpheme: ish - root noun (C); -chi noun-deriving affix \$[i,1-1]C(A[i]); -lar – plural affix; (X2) - possessive affix; (X3) - case affix, as defined in. Thus, the mathematical model (MM) for the <ishchilarimizdan> is constructed as follows: <ish + chi + lar + imiz + dan>.

$$\{s_{[j,1-h]}C_{[j]} \oplus \downarrow s_{[i,1-1]}C(A_{[i]}) \oplus \downarrow X \oplus \downarrow s_{[j1,1-1]}C_{[i1]} \oplus \downarrow s_{[i1,1-5]}X_{[i1]}$$

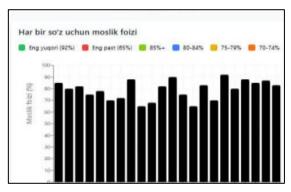
In (2), based on the general form of the new mathematical model, Table 3 presents the complex new mathematical models (MM) and weight coefficients (V3) for each of the 22 noun-deriving affixes \$[i,1-22]C(A[i]) in Uzbek. The translations into English of 22 Uzbek words formed by combining a root noun with the affixes \$[i,1-22]C(A[i]), together with their new mathematical models (MM) and weight coefficients (V3), are also provided in Table 3 as examples.

Table IV: New Mathematical Models and Weight Coefficients of Compound Words in Uzbek and English

Mathematical Model (MM) of a Compound Word in Uzbek	V2 in Uzbek	V2 in English	Mathematical Model (MM) of the Translated Compound Word in English	
$\begin{array}{c} \$_{\mathbf{j},\mathbf{i}-\mathbf{h}_{\mathbf{j}}}C_{\mathbf{j}\mathbf{j}} \oplus \downarrow \$_{[i,1-\mathbf{h}_{\mathbf{i}}]}C(A_{[i]}) \oplus \downarrow X \\ \oplus \downarrow \$_{[j,1-1_{\mathbf{i}}]}X2_{[j]} \oplus \downarrow \$_{[k,1-5]}X3_{[k]} \end{array}$	0.850101010104010201	0.85045601010401		
	0.850102010104010201	0.85045601020401		
$\begin{array}{c} \$_{\mathbf{ij},1-\mathbf{h} }\mathbf{C}_{\mathbf{ij} } \bigoplus \downarrow \$_{[i2,1-\mathbf{h}1]}\mathbf{C}(\mathbf{A}_{[i2]}) \bigoplus \downarrow \mathbf{X} \\ \bigoplus \downarrow \$_{[j1,1-10]}\mathbf{X}2_{[\mathbf{j}]} \bigoplus \downarrow \$_{[k,1-5]}\mathbf{X}3_{[\mathbf{k}]} \end{array}$	0.850105010104010201	0.85045601010401	$ \begin{cases} s_{[i,1-58]}D_{[i]} \oplus \downarrow s_{[i,1-7]}M10(C_{[i]}) \oplus \downarrow s_{[i,1-h1]} \\ C(A_{[i]1}) \oplus \downarrow s_{[i,1,-2]}X_{[i]1} \end{cases} $	
$\begin{array}{c} \$_{ij,i-h}_iC_{ij} \bigoplus \downarrow \$_{[i3,1-h1]}C(A_{[i3]}) \bigoplus \downarrow X \$_{[j,1-10]} \\ \bigoplus \downarrow X2_{[i]} \bigoplus \downarrow \$_{[k,1-5]} X3_{[k]} \end{array}$	0.850120010104010201	0.85045601010401	(* *[ii])	
$ \begin{array}{c} \$_{\mathbf{j},1-\mathbf{h}_{\mathbf{l}}}C_{\mathbf{j}\mathbf{j}} \oplus \downarrow \$_{\mathbf{j},1-\mathbf{i}_{\mathbf{l}}}C(A_{\mathbf{j}+\mathbf{d}}) \oplus \downarrow X \oplus \downarrow \$_{\mathbf{j},1-1_{0}} \oplus \downarrow X2_{\mathbf{j}\mathbf{j}} \oplus \downarrow \\ \$_{\mathbf{j},1-5_{\mathbf{l}}}X3_{\mathbf{j}\mathbf{k}} \end{array} $	0.850115010104010201	0.85045601010401		
	0.850116010104010201	0.85045601030401		
	0.850118010104010201	0.85045601040401	$ \begin{array}{c} \$_{[i,1-58]}D_{[i]} \bigoplus \downarrow \$_{[j,1-7]}M10(P_{[j]}) \bigoplus \downarrow \$_{[i1,1-h1]} \\ C(A_{[i1]}) \bigoplus \downarrow \$_{[j1,1-2]}X_{[j1]} \end{array} $	
$\begin{array}{c} \$_{\mathbf{j},\mathbf{i}-\mathbf{h}_{\mathbf{j}}}C_{\mathbf{j}\mathbf{j}} \oplus \downarrow \$_{\mathbf{j},\mathbf{i}-\mathbf{i}_{\mathbf{j}}}C(A_{\mathbf{i}7}) \oplus \downarrow X \oplus \downarrow \$_{[\mathbf{j},1-10]} \\ \oplus \downarrow X2_{[\mathbf{j}]} \oplus \downarrow \$_{[\mathbf{k},1-5]} X3_{[\mathbf{k}]} \end{array}$	0.850117010104010201	0.85045601050401		
$\begin{array}{c} \$_{[\mathbf{j},1-\mathbf{h}]}C_{[\mathbf{j}]} \oplus \downarrow \$_{[\mathbf{j},1-\mathbf{i}]}C(A_{[18]}) \oplus \downarrow X \\ \oplus \downarrow \$_{[\mathbf{j},1-10]} X2_{[\mathbf{j}]} \oplus \downarrow \$_{[\mathbf{k},1-5]} X3_{[\mathbf{k}]} \end{array}$	0.850108010104010201	0.85045601010401	$ \begin{array}{c} \$_{[i,1\text{-}58]}D_{[i]} \oplus \downarrow \$_{[j,1\text{-}7]}M10(C_{[j]}) \oplus \downarrow \$_{[i1,1\text{-}h1]} \\ C_{[i1]} \oplus \downarrow \$_{[j1,1\text{-}h1]}C(A_{[j1]}) \oplus \downarrow \$_{[i2,1\text{-}2]}X_{[i2]} \end{array} $	
$\begin{array}{c} \$_{[\mathbf{j},1-\mathbf{h}]}C_{[\mathbf{j}]} \oplus \downarrow \$_{[\mathbf{j},1-\mathbf{i}]}C(A_{[\mathbf{i}9]}) \oplus \downarrow X \\ \oplus \downarrow \$_{[\mathbf{j},1-10]} X2_{[\mathbf{j}]} \oplus \downarrow \$_{[\mathbf{k},1-5]} X3_{[\mathbf{k}]} \end{array}$	0.850119010104010201	0.85045601010401		
$\begin{array}{c} \$_{\mathbf{j},\mathbf{i}-\mathbf{h}_{\mathbf{i}}}\mathbf{C}_{\mathbf{i}\mathbf{j}} \bigoplus \downarrow \$_{\mathbf{j},\mathbf{i}-\mathbf{i}}\mathbf{C}(\mathbf{A}_{[\mathbf{i}10]}) \bigoplus \downarrow \mathbf{X} \\ \bigoplus \downarrow \$_{[\mathbf{j},\mathbf{i}-\mathbf{i}0]} \mathbf{X2}_{[\mathbf{j}]} \bigoplus \downarrow \$_{[\mathbf{k},\mathbf{i}-5]} \mathbf{X3}_{[\mathbf{k}]} \end{array}$	0.850121010104010201	0.85045601010401	$C_{[i1]} \bigoplus \downarrow \$_{[j1,1-h1]}C(A_{[j1]}) \bigoplus \downarrow \$_{[i2,1-2]}X_{[i2]}$	
$\begin{array}{c} \$_{\mathbf{j},\mathbf{i}-\mathbf{h} }C_{\mathbf{j}\mathbf{j}} \oplus \downarrow \$_{\mathbf{j},\mathbf{i}-\mathbf{i} }C(A_{[i11]}) \oplus \downarrow X \\ \oplus \downarrow \$_{[i,l-10]} X2_{[i]} \oplus \downarrow \$_{[k,l-5]} X3_{[k]} \end{array}$	0.850103010104010201	0.85045601010401		
$\begin{array}{c} \$_{[i,1-i]}C_{[i]} \oplus \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ $	0.850104010104010201	0.85045601010401		
	0.850109010104010201		$\$_{[i,1-58]}D_{[i]} \oplus \downarrow \$_{[j,1-1]}D(D4_{[j]}) \oplus \downarrow \$_{[j1,1-h1]}$	
$\begin{array}{c} \textbf{\$}_{\textbf{[j,1-h]}}\textbf{C}_{\textbf{[j]}} \oplus \downarrow \textbf{\$}_{\textbf{[j,1-i]}}\textbf{C}(\textbf{A}_{[i14]}) \oplus \downarrow \textbf{X} \oplus \downarrow \textbf{\$}_{\textbf{[j,1-10]}}\textbf{X2}_{\textbf{[j]}} \\ \oplus \downarrow \textbf{\$}_{\textbf{[k,1-5]}}\textbf{X3}_{\textbf{[k]}} \end{array}$	0.850107010104010201	0.85045601030401	$C(A_{[j1]}) \oplus \downarrow \$_{[i2,1-2]}X_{[i2]}$	
	0.850110010104010201	0.85045601010401		
$\begin{array}{c} \textbf{\$}_{\textbf{[j,1-h]}}\textbf{C}_{\textbf{[j]}} \oplus \downarrow \textbf{\$}_{\textbf{[j,1-i]}}\textbf{C}(\textbf{A}_{[i16]}) \oplus \downarrow \textbf{X} \\ \oplus \downarrow \textbf{\$}_{[j,1-10]}\textbf{X2}_{[j]} \oplus \downarrow \textbf{\$}_{[k,1-5]}\textbf{X3}_{[k]} \end{array}$	0.850111010104010201	0.85045601010401		
$ \begin{array}{c} \$_{[j,1\text{-}h_i]}C_{[j]} \oplus \downarrow \$_{[j,1\text{-}i]}C(A_{[i17]}) \oplus \downarrow X \$_{[j,1\text{-}10]} X2_{[j]} \\ \oplus \downarrow \$_{[k,1\text{-}5]} X3_{[k]} $	0.850106010104010201	0.85045601010401		
$\begin{array}{c} \textbf{\$}_{[j,1\text{-}h]}C_{[j]} \oplus \downarrow \textbf{\$}_{[j,1\text{-}i]} C(A_{i18}) \oplus \downarrow X \textbf{\$}_{[j,1\text{-}10]} X2_{[j]} \oplus \downarrow \textbf{\$}_{[k,1\text{-}5]} \\ X3_{[k]} \end{array}$	0.850112010104010201	0.85045601010401	$ \begin{array}{c} \$_{[i,1-58]}D_{[i]} \oplus \downarrow \$_{[j,1-1]}D(D4_{[j]}) \oplus \downarrow \$_{[i1,1-h1]}C_{[i1]} \\ \oplus \downarrow \$_{[i1,1-h1]}C(A_{[j1]}) \end{array} $	
	0.850113010104010201	0.85045601010401	$\bigoplus \downarrow \$_{[i2,1\cdot2]}X_{[i2]}$	
	0.850114010104010201	0.85045601010401	$ \begin{split} \$_{[i,1-58]}D_{[i]} & \bigoplus \downarrow \$_{[j,1-1]}D(D4_{[j]}) \bigoplus \downarrow \$_{[i1,1-7]}M(C_{[i1]}) \bigoplus \downarrow \$_{[i1,1-h1]}C_{[j1]} \bigoplus \downarrow \$_{[i2,1-h1]} \\ & C(A_{[i2]}) \bigoplus \downarrow \$_{[j2,1-2]}X_{[j2]} \end{split} $	
$\begin{array}{c} \$_{\mathbf{[j,1-h]}}\mathbf{C}_{\mathbf{[j]}} \oplus \downarrow \$_{\mathbf{[j,1-i]}}\mathbf{C}(\mathbf{A}_{[i21]}) \oplus \downarrow \mathbf{X} \$_{\mathbf{[j,1-10]}} \mathbf{X2}_{\mathbf{[j]}} \\ \oplus \downarrow \$_{\mathbf{[k,1-5]}} \mathbf{X3}_{\mathbf{[k]}} \end{array}$	0.850122010104010201	0.85045601010401		







[Fig.4: Percentage Correspondence Diagram of Each **Compound Word Constructed in Uzbek to English**]

In Figure 4 above, the 22 affixes \$[i,1-22]C(A[i]) given in Table 4 were combined in the form <root \bigoplus affix \bigoplus X \bigoplus X2 ⊕ X3> to construct compound words, and new mathematical models (MM) of these compound words were developed along with their English translations. Figure 4 illustrates the percentage of correspondence between the compound words presented in Table 4 across the two languages. The degree of equivalence between Uzbek noun-deriving affixes \$[i,1-22]C(A[i]) and their English counterparts is relatively high, averaging 83.2%. The highest level of correspondence was observed in the affix denoting professions.

Table V: 1.2 Affixes that Form Noun Names

O'ztnnya	(mm) va v3	Itmymea	(mm) va v3
-don	$_{[i,1-h]}^{C(A_{[j]})}$	-pot	$\{i,i-h\} C(A_{[i]})$
	0.850102		0.850102
-noma	$_{[i,1-h]}C(A_{[j1]})$	-ation ₁	$C(A_{[1]}), C(A_{[2]})$
	0.850202	-in ₂	0.850202, 0.850302
-poya	$_{[i,1-h]}C(A_{[j2]})$	-case	$_{[i,1-h]}C(A_{[i]})$
	0.850302		0.850402
-bon	$_{[i,1-h]}C(A_{[j3]})$	-	$_{[i,l-h]}C_{[i]}$
	0.850402		0.85

An analysis of noun-forming affixes in Uzbek and their English correspondences. Based on the data presented in Table 5, the correspondence of Uzbek noun-forming affixes to English affixes was examined. The Uzbek affix <-don> shows a high degree of similarity to the English <-pot> affix, particularly in compound word formation, with an approximate correspondence of 80%. The affix <-noma> demonstrates a moderate alignment with English affixes, with a correspondence of 60%. The Uzbek affix <-poya> corresponds closely to the English <-case> affix, achieving 85% alignment. In contrast, no English equivalent exists for the Uzbek <-bon> affix.

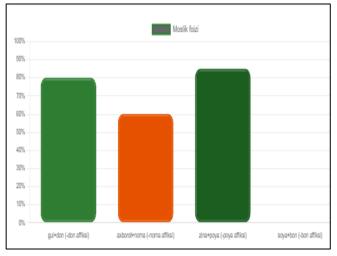


Fig.5: The Degrees of Correspondence and Non-Correspondence

In Figure 5, the degrees of correspondence and noncorrespondence of affixes between the two languages are presented in the diagram below, expressed as percentage values.

Table VI: Mathematical Models of Complex Words Formed through Thing-Naming Affixes in the Uzbek Language

Mathematical Model (MM) of a Compound Word in Uzbek	V2 in Uzbek	V2 in English	Mathematical Model (MM) of the Translated Compound Word in English
$ \begin{array}{c} \$_{[i,1-h]}C_{[i]} \bigoplus \downarrow \$_{[j,1-h]} \ C(A_{[j]}) \bigoplus \downarrow X \bigoplus \\ \downarrow \$_{[i1,1-10]} \ X2_{[i1]} \bigoplus \downarrow \$_{[j1,1-5]} \ X3_{[j1]} \end{array} $	0.850102010104010201	0.85045601030401	$\$_{[i,1-58]}D_{[i]} \oplus \downarrow \$_{[j,1-7]}M10(P_{[j]}) \oplus \downarrow \$_{[i1,1-h]}C_{[i1]} \oplus \downarrow X_1$
$ \begin{array}{c} \$_{[i,1-h]}C_{[i]} \bigoplus \downarrow \$_{[i,1-h]}C(A_{jl}) \bigoplus \downarrow X \bigoplus \downarrow \\ \$_{[i1,1-10]} \ X2_{[i1]} \bigoplus \downarrow \$_{[j1,1-5]} \ X3_{[j1]} \end{array} $	0.850202010104010201	0.85045601010401	
$\S_{[i,1-h]} C(A_{j2})$	0.850302010104010201	0.85045601010401	$\$_{[i,1-58]}D_{[i]} \oplus \downarrow \$_{[j,1-7]}M10(P_{[j]}) \oplus \downarrow \$_{[i1,1-h]}C_{[i1]} \oplus \downarrow X_1$
$\S_{[i,1-h]} C(A_{j3})$	0.850402010104010201	0.85045601010401	$\$_{[i,1\text{-}58]}D_{[i]} \bigoplus \downarrow \$_{[j,1\text{-}7]}M10(P_{[j]}) \bigoplus \downarrow \$_{[i1,1\text{-}h]}C_{[i1]} \bigoplus \downarrow X_{[1]}$

In Table 6, examples of words in Uzbek are presented that are formed by attaching noun-deriving affixes \$[j,1h]C(A[i])\$ to the root (C), thereby generating new lexical items—the combination of root and affix results in the formation of compound words. While Table 3 illustrated the structural model of compound word formation, Table 6 likewise demonstrates the construction of compound words and their translation into English through newly developed mathematical models. The outcomes of this process are reflected in Figure 6, which presents the percentage values with precise indicators.

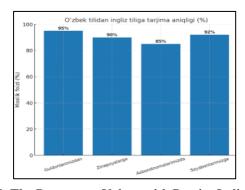


Fig.6: The Percentage Values with Precise Indicators

In the upper section of this article, we presented a new mathematical model for noun-



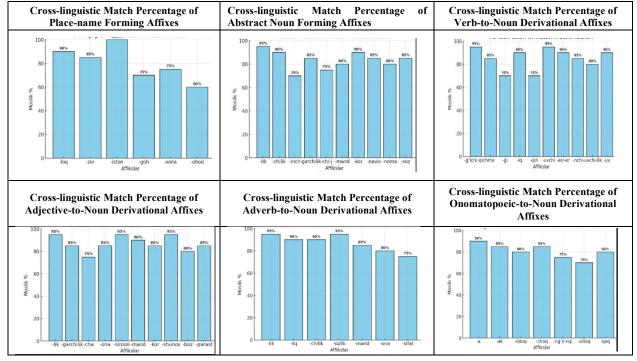
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to-noun derivation, where the affix structure \$[i,1-22]C(A[i]) is attached to a simple root to generate new words. Furthermore, we developed corresponding models for complex word formation derived through the same affixes \$[i,1-22]C(A[i]), which are demonstrated in Table 3. In addition to this, new mathematical models were also constructed for the affixes \$[i,1-4]C(A[j])\$, like those of \$[i,1-22]C(A[i]), and their cross-linguistic equivalence percentages are illustrated in the diagrams provided above. Following the analysis of Uzbek affixes that derive nouns from nouns and affixes that generate object names, we also developed new mathematical models for other derivational categories. These include:

place-name forming affixes - C(A_[n])

abstract noun forming affixes - $C(A_{[i]})$ verb-to-noun derivational affixes - $C(AG_{[i]})$ adjective-to-noun derivational affixes - $C(AP_{[i]})$ adverb-to-noun derivational affixes - $C(An_{[i]})$ affixes deriving nouns from onomatopoeic words - $C(AX5_{[i]})$

For each of these categories, corresponding English equivalent affixes were identified, and the percentage of equivalence between the two languages was calculated. The results are presented in the form of diagrams, similar to those given above. All percentages and comparative values were obtained based on our own cross-linguistic analysis of Uzbek and English affixal systems.



[Fig.8: The Results Presented Above, particularly]

Based on the results presented above, particularly those illustrated in Figure 8, new mathematical models of affixes were constructed for both languages, and their analysis was carried out. This approach provides a crucial scientific foundation for the future development of high-quality machine translation. Indeed, only when each affix in the EVX text is accurately translated into the EVIX text can the original meaning of words be fully preserved, thereby ensuring a reliable and semantically faithful translation of the entire text.

IV. CONCLUSION

In this study, we paid special attention to the morphemes of words in two natural languages when creating scientific computer translation from English to Uzbek, and analyzed, based on examples and program results, the extent to which word-forming affixes correspond or do not correspond between the two languages. Based on the results presented above, it can be stated that the degree of correspondence of English noun-forming affixes with Uzbek words and affixes is expressed in percentages. According to the mathematical model, the English affix "-er" shows a high level of

correspondence with Uzbek noun-forming affixes. The length of an affix affects its weight (longer affixes have slightly higher weights). This program performs affix analysis through mathematical models and evaluates interlingual correspondence. The mathematical model is a valuable tool for interlingual translation and linguistic research. There are similarities among affixes belonging to each word class, but some structural and syntactic differences are also observed. A morphological approach through mathematical formulas is applied. These formulas are implemented in real translation systems through embedding + attention + decoder blocks. Mathematical models based on the expandable input language provide the following advantages for machine translation: affix-based translation increases grammatical and semantic correspondence; it determines the function of each morpheme in the text and grammatically corrects the resulting translation; separate processes for correspondence checking can be identified

through independent word class analysis; high accuracy is achieved by determining





mathematical models and weight coefficients for each affix.

DECLARATION STATEMENT

I must verify the accuracy of the following information as the article's author.

- Conflicts of Interest/ Competing Interests: Based on my understanding, this article has no conflicts of interest.
- Funding Support: This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- Ethical Approval and Consent to Participate: The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- Data Access Statement and Material Availability: All the new mathematical models presented in this article are based on the work of Prof. Khakimov M.Kh. of the National University of Uzbekistan, namely: 21. Khakimov, M.Kh. Technology of Multilingual Modelled Computer Translator. Monograph // LAP LAMBERT Academic Publishing, Riga, 2019, 174 p.. In this monograph, an expandable input language is introduced for natural language processing in multilingual computer translation. Based on this expandable input language, general mathematical models of words and sentences are developed. In the present article, we build new mathematical models of affixes through the analysis of affixes in two natural languages (Uzbek and English) to create a high-quality machine translation system from Uzbek to English. Using these newly constructed mathematical models, the grammatical, semantic, and syntactic rules of natural languages can be formalized in a way that is understandable to the computer. This has been described in detail in both the previous and current articles. The datasets and new mathematical models generated and analyzed during this study are available from the corresponding author upon reasonable request.
- Author's Contributions: The authorship of this article is contributed solely.

REFERENCES

- Khakimov, Sh. O., Bekova, V. A., & Olimova, N. K. (2023). Developing a model of an English-Uzbek electronic translator based on rule-based machine translation. AIP Conference Proceedings, 2931(1), 080026. DOI: https://doi.org/10.1063/5.0104005
- Lin L., Liu J., Zhang X., Liang X. Automatic translation of spoken English based on improved machine learning algorithm // Journal of Intelligent & Fuzzy Systems. – 2021. – Vol. 40, №2. – P. 2385-2395. – DOI: https://dx.doi.org/10.3233/JIFS-189234.
- Zhang G. Research on the efficiency of intelligent algorithms for English speech recognition and sentence translation // Inform An Int J Comput Inform. – 2022. – Vol. 45, №2. – P. 309-314. – DOI: https://dx.doi.org/10.31449/inf.v45i2.3564.
- Wen H. Intelligent English translation mobile platform and recognition system based on support vector machine // Journal of Intelligent & Fuzzy Systems. – 2020. – Vol. 38, №153. – P. 1-12. – DOI: https://dx.doi.org/10.3233/JIFS-179788.
- Dandapat S., Federmann C. Iterative data augmentation for neural machine translation: a low resource case study for English-Telugu // Vol. Proceedings of the 21st Annual Conference of the European Association

- for Machine Translation, (Alacant, Spain), European Association for Machine Translation. 2018. May 28-30, P. 287-292. https://aclanthology.org/2018.eamt-main.29/
- Lin X, Liu J, Zhang J, Lim S. A novel beam search to improve neural machine translation for English-Chinese // Comput Mater Contin (Engl). – 2020. –Vol.65, №1 P. 387-404.
 - DOI: https://dx.doi.org/10.32604/cmc.2020.010984
- Choi H, Cho K, Bengio Y. Context-dependent word representation for neural machine translation// Comput Speech Lang. – 2017. –Vol.45, P. 149-160. https://dx.doi.org/10.18653/v1/P16-1100.
- M. Chen, "Trust, understanding, and machine translation: The task of translation and the responsibility of the translator," AI & Society, vol. 39, no. 5, pp. 2307–2319, May 2023, DOI: https://doi.org/10.1007/s00146-023-01681-6
- Nunes Vieira, L., O'Sullivan, C., Zhang, X., & O'Hagan, M. (2022). Machine Translation in Society: Insights from UK Users. *Language Resources and Evaluation*, 57(2), 893–914.
 DOI: https://doi.org/10.1007/s10579-022-09589-1
- Matlatipov, S., Tukeyev, U., Aripov, M. Towards the Uzbek language endings as a language resource. In: Hernes, M., Wojtkiewicz, K., Szczerbicki, E. (eds.) ICCCI 2020. CCIS, vol. 1287, pp. 729–740. Springer, Cham (2020).
 DOI: https://doi.org/10.1007/978-3-030-63119-2 59
- Yergesl, B., Bekmanova, G., Sharipbay, A., Yergesh, M.: Ontology-based sentiment analysis of Kazakh sentences. In: Gervasi, O., et al. (eds.) ICCSA 2017. LNCS, vol. 10406, pp. 669–677. Springer, Cham (2017). DOI: https://doi.org/10.1007/978-3-319-62398-6 4
- Khakimov, M.Kh. The Ministry of Justice of the Republic of Uzbekistan.
 Official Bulletin Journal. No. 10 (238), 2022, pp. 110-113. Patent No.
 IAP 07121,
 https://americanjournal.org/index.php/ajtas/article/download/2971/280
 4//989
- Khakimov, M.Kh. Technology of Multilingual Modelled Computer Translator. Monograph // LAP LAMBERT Academic Publishing, Riga, 2019, 174 p.
- 14. Mersaid Aripov, Muftakh Khakimov, Sanatbek Matlatipov, and Ziyoviddin Sirojiddinov. Analysis and Processing of the Uzbek Language on the Multilingual Modelled Computer Translator Technology. In: Vetulani, Z., Paroubek, P., Kubis, M. (eds) Human Language Technology. Challenges for Computer Science and Linguistics. Pp 81–95 LTC 2019. Lecture Notes in Computer Science, vol 13212. Springer, Cham.

DOI: https://doi.org/10.1007/978-3-031-05328-3 6

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No.4(58), 2024. "Kompyuter tarjimasi uchun olmosh so'z turkumining ingliz-o'zbek yo'nalishidagi tahlili va matematik modellari" – Proceedings of the

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Republican Scientific-Practical Conference "Modern Problems and Prospects of Applied Mathematics", Qarshi, 2024, p.629. "Ingliz va oʻzbek tillaridagi mos kelgan affiksatsiyalarning vaznlari va vaznlar farqining mashina tarjimasidagi ahamiyati" – VI International Conference. "Analysis and Models of Pronouns in English—Uzbek Computer Translation" – AIP Conference Proceedings. "Computer Translation from English to Uzbek: New Mathematical Models" – Problems of Computational and Applied Mathematics, No.2/2(66), 2025. "Kompyuter tarjimasi uchun olmosh soʻz turkumining oʻzbek—ingliz yoʻnalishidagi tahlili va matematik modellari" – QarDU Xabarlari, Scientific-Theoretical, Methodological Journal, Vol.3(2), 2024. Additionally, one article has been accepted for publication in the AIP Journal (No. 3377).

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