Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

ERROR ANALYSIS IN MULTILINGUAL TRANSLATION PRACTICES

Erkinjon Satibaldiev
Senior Teacher Uzbek State World Languages University

Abstract:
Error analysis plays a critical role in improving multilingual translation quality between English and Russian. This study examines translation errors in both human and machine translation (MT) contexts (specifically Google Translate and DeepL), focusing on English–Russian and Russian–English directions. We adopt an IMRAD structured approach. In the Introduction, we highlight the significance of error analysis and present key theoretical frameworks such as contrastive analysis, error taxonomy, and interference theory. The Methods section outlines our comparative approach, combining contrastive linguistic analysis with an error taxonomy to classify errors (grammatical, lexical, semantic, pragmatic) in human translator outputs and MT outputs. In Results, we identify common error types in both EN→RU and RU→EN translation, supported by examples from published studies and corpus analyses. Typical errors include grammatical mismatches (e.g., articles, agreement, word order), lexical mistranslations (false friends, idioms), semantic inaccuracies, and pragmatic/contextual misrenderings. A comparison between human and MT practices reveals that while human translators are influenced by linguistic interference, MT systems often struggle with context and idiomatic usage. In the Discussion, we consider the practical implications of these findings for translators, educators, and MT developers. The study underscores the importance of error analysis for enhancing translation training and improving machine translation systems.

Keywords: Error analysis; English–Russian translation; Machine translation; Human translation; Contrastive analysis; Interference.

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

Introduction

Translation between English and Russian is a linguistically challenging task due to significant structural and cultural differences between the two languages. English is an analytic language with fixed word order and articles, whereas Russian is a synthetic, inflectional language with free word order and no articles. These differences often lead to translation difficulties and errors. **Error analysis** in multilingual translation is therefore crucial for diagnosing issues and improving quality. By systematically examining errors, researchers can identify patterns of mistakes and their causes, ultimately informing better translation practices and tools. Error analysis has become increasingly significant in the context of growing cross-cultural communication and the rise of machine translation.

Several theoretical frameworks inform the analysis of translation errors. **Contrastive analysis (CA)** is the systematic study of two languages to predict potential difficulties by identifying structural differences and similaritiesn. Early contrastive linguistics (e.g., Lado's work in the 1950s) posited that many errors arise from differences between native and target language structures, and that comparing English and Russian can reveal likely points of interference. For example, English uses the construction "there is/are" for existence, while Russian often uses different structures (such as *есть* or impersonal phrases). Contrastive analysis helps anticipate that an English speaker might calque "There are many rooms in the museum" as *Музей имеет много комнат* ("The museum has many rooms"), which is grammatical but unnatural in Russian. Identifying such divergences through CA provides a foundation to understand error sources.

Closely related is the concept of **interference** (negative transfer). Interference theory examines how a translator's native language influences the target language output. When translators (or learners) subconsciously apply rules or word choices from their first language, **interlingual errors** can occur. For instance, Russian has flexible word order, so Russian speakers learning English may produce sentences with subject–verb–object out of typical English order, reflecting Russian patterns. Conversely, English speakers translating into Russian might maintain English sentence structures or omit required inflections. Research by Galkina and Radyuk (2019) documents such interference-driven errors in student translations. They note that many Russian learners of English misorder elements or misuse verb tenses due to native language influence, while American learners

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

of Russian often directly translate English constructions and ignore Russian grammatical nuances. Interference can affect various linguistic levels – grammatical (syntax, morphology), lexical (word choice), even punctuation – and is a root cause of numerous translation errors.

Another important framework is **error taxonomy** in translation quality assessment. Rather than only attributing errors to cross-linguistic influence, error taxonomies classify the types of errors regardless of cause. One influential taxonomy by Koponen (2010) categorizes translation errors into several types, such as *omitted content*, *untranslated content*, and *mistranslated content*, among others. Such frameworks allow a structured analysis of errors by type (e.g., grammatical, lexical, semantic, pragmatic errors) and severity. In recent years, these taxonomies have been applied to both human and machine translation output to systematically identify error patterns. By combining contrastive analysis (to explain why errors occur) with error classification (to describe what the errors are), researchers can gain a comprehensive understanding of translation pitfalls in the English–Russian pair.

The importance of error analysis is further underscored by practical needs. English and Russian are widely translated languages (in diplomacy, literature, science, etc.), and ensuring high-quality translation between them has broad implications. Misinterpretations or mistakes can lead to loss of meaning or even critical misunderstandings. In professional settings, *translation quality assessment* relies on detailed error analysis to provide feedback to human translators and to evaluate MT systems. As machine translation systems like Google Translate and DeepL are increasingly used for English–Russian translation, comparing their error profiles to human translations has become a focus of research. The following sections outline our methodology for examining errors in both human and machine translations, present key results on error types in each direction, and discuss what these findings mean for translation practice and research.

Methods

This study employs a comparative, qualitative approach to analyze errors in English–Russian translation, examining both human and machine translation outputs. We combined **contrastive linguistic analysis** with an established **error taxonomy** to categorize and compare errors. First, we conducted a literature

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

review and gathered examples of translation errors from scholarly studies and corpora. Sources included error-annotated translation corpora (for human translator errors) and evaluations of MT systems on English–Russian tasks. For human translation, we drew on analyses of learner and professional translations (e.g., the Russian Learner Translator Corpus and case studies like Galkina & Radyuk (2019)), which provide documented errors made by translators in EN↔RU tasks. For machine translation, we collected data from recent evaluations of Google Translate and DeepL for English–Russian and Russian–English translations, supplemented by findings from research articles that performed MT error analysis.

We adopted **error classification criteria** inspired by Koponen's (2010) framework and other translation quality metrics. In practice, each identified error was classified into one of several categories: **grammatical errors** (violations of grammar rules such as tense, agreement, word order), **lexical errors** (mistakes in word choice or terminology, including false friends), **semantic errors** (mistranslations that distort or omit the meaning of the source), and **pragmatic errors** (issues with usage, register, or cultural context). Some errors fell into multiple categories; for example, a mistranslated idiom could be seen as a lexical semantic error with pragmatic implications. We also noted whether an error likely stemmed from interference (transfer from source-language patterns) or other factors (such as lack of target-language knowledge or system limitations in MT).

For the machine translation component, we specifically compared Google Translate and DeepL. We used a sample of sentences and short texts translated by both systems in both directions (EN→RU and RU→EN) and applied the same error annotation scheme to their outputs. This was complemented by reported findings from previous comparative studies of these tools. For instance, we considered studies that quantified error frequencies or types in Google vs DeepL outputs. Human translations (from professionals or advanced students) of similar texts were used as a benchmark to highlight differences in error patterns. All examples and error instances were documented and referenced from published research to ensure authenticity. The results section synthesizes these findings, presenting common error types with illustrative examples, and quantifies certain error trends (e.g., which types are most frequent) as reported in the literature.

Overall, the methodology is exploratory and descriptive, aiming to map out the landscape of translation errors in the English–Russian context rather than to

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

evaluate a specific translation system or cohort. By triangulating evidence from multiple studies and corpora, we ensure that the identified error patterns are representative and robust. This approach allows us to compare human and machine translations on equal footing, using consistent criteria, and to discuss error trends in a scholarly manner.

Results

Common Error Types in English–Russian Translation

Analysis of the data reveals several prevalent error types in English–Russian translation, observed in both human translator output and MT output. We organize the findings by error category, highlighting differences between **English→Russian (EN→RU)** and **Russian→English (RU→EN)** directions.

Grammatical Errors: Grammatical mismatches are a major source of errors. In EN→RU translation, a frequent issue is handling Russian inflectional grammar. Translations produced by non-native speakers or MT often show incorrect case endings, verb aspect errors, or agreement errors. For example, Russian has grammatical gender and complex case requirements; a machine translation might produce an ungrammatical sentence by using the wrong case after a preposition or failing to adjust an adjective to match a noun's gender/number. Human translators, especially learners, also struggle with such features. Galkina and Radyuk (2019) report that American students translating into Russian often made errors with **verb aspect** and **infinitive constructions**, since English aspect (progressive, perfect) does not map directly to Russian's perfective/imperfective system. One common error was translating English infinitival phrases word-for-word into Russian where they are ungrammatical or require a different structure. Similarly, in RU→EN translation, **article usage** is a persistent problem. Russian has no articles, so Russian translators frequently omit "the" or "a" where required in English, or insert them incorrectly. This interlingual interference leads to sentences like *"She entered Ø university"* instead of *"She entered the university,"* affecting grammatical correctness. Another grammatical area is **word order**: Russian's flexible word order can carry information about topic or emphasis, whereas English relies on a stricter SVO order. Russian speakers may produce English sentences with unconventional order (e.g., *"At five in the morning woke up the city"* instead of *"The city woke up at five in the morning"*), which can confuse meaning. On the other hand, English speakers translating to Russian

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

might calque English structures too directly. A documented example is overusing the verb "to have" in existential statements. Instead of using impersonal constructions, translators write *Город имеет много ресторанов* ("The city has many restaurants") as a direct rendition of "The city has many good restaurants," where a native Russian would say *В городе много хороших ресторанов* ("In the city, [there are] many good restaurants"). Such errors, noted as **syntactic interference**, illustrate how grammar structures from the source language improperly carry over to the target.

Lexical and Semantic Errors: These involve choosing incorrect words or misinterpreting meanings. **False friends** and **polysemous words** are a notorious source of error between English and Russian. For EN→RU, a human translator might select a Russian word that looks similar to the English but has a different meaning (e.g., translating English "artist" as Russian *артист*, which actually means "performer" not a painter, or "actual" as *актуальный* which means "relevant"). Machine translation systems also fall for false friends or literal translations if context is not clear. **Mistranslation of idioms and figurative language** is another common semantic error. English idioms like "spill the beans" or Russian idioms like "вешать лапшу на уши" (literally "hang noodles on the ears," meaning to deceive) often get translated word-for-word by MT, producing nonsensical output. Human translators are better at recognizing idioms, but if they are inexperienced or unaware of a particular expression, they might also produce awkward literal translations. Studies have found that both Google Translate and DeepL struggle with idiomatic and cultural terms, frequently leading to mistranslations. For example, Strikou (2024) observed that DeepL misinterpreted the Russian term *леший* (a mythological forest spirit) as "lion" in one literary context, presumably by choosing a superficially similar word. This **lexical error** severely distorts the meaning (semantic error), showing that even advanced MT can misinterpret uncommon words or cultural references. In RU→EN translation, lexical errors often involve misusing verb phrases or selecting words with the wrong connotation. A Russian translator might render *решить проблему* as "decide the problem" instead of "solve the problem," because the verb *решить* means both "decide" and "solve" depending on context. Such subtle semantic distinctions are a known pitfall. Named entities (proper nouns, names of organizations, etc.) also pose challenges. An error analysis by Shimorina et al. (2019) of an English-to-Russian MT system found that **80%** of translated

Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

sentences contained at least one error, and notably **53%** of all errors were related to **named entities**. This indicates that transliteration or correct handling of names and titles (e.g., preserving Russian name endings or translating geographical names correctly) is a major issue, particularly for MT. Human translators generally handle names better (by adhering to standard transliteration conventions), but MT systems may mistransliterate or confuse proper nouns with common nouns.

Pragmatic and Contextual Errors: These errors involve the appropriateness of the translation in context – including register (formality), style, and cultural nuances. English and Russian differ in forms of address (e.g., English "you" vs Russian *ты*/*Вы* informal/formal distinction), levels of directness, and other pragmatic conventions. A common pragmatic error in RU→EN human translation is overly formal or archaic tone, as Russian academic or official style can sound overly stiff if translated literally into English. For instance, a Russian official phrase might translate literally as "Upon carrying out the experiment, conclusions were drawn…" which in English would be more naturally "After the experiment, we concluded…". Conversely, an MT might produce an English sentence that is grammatically correct but pragmatically odd or ambiguous due to lack of context understanding. Both Google Translate and DeepL have been noted to sometimes misuse formal vs informal address in EN↔RU. For example, given a sentence with *вы* (formal "you"), an MT might translate it as a first name or drop the formality in English when it should perhaps be preserved through tone or by adding a formal salutation. Human translators usually catch such nuances, though errors can occur if context is missing or misinterpreted. Another pragmatic aspect is **genre conventions**: what might be acceptable phrasing in a legal document could be incorrect in a casual text. A study by Atabekova (2023) on legal translation errors found numerous issues in how legal terms and references were translated into English. Specifically, professional translators working on a Russian legal code's English version introduced errors such as wrong legal terminology and grammar (17% of errors were grammatical, 14% lexical) not conforming to target genre conventions or failing to find an equivalent legal concept. Pragmatically, this means the translation, while perhaps intelligible, did not function properly as a legal text in English. Atabekova's analysis highlights that beyond linguistic accuracy, **domain-specific adequacy** is crucial –

translators must consider how terms are used in the target language's legal system, not just do direct dictionary translation.

Human vs Machine Translation Error Patterns

Comparing human and machine translation practices, we observe both overlaps and differences in error patterns. **Human translators** (especially trainees or non-experts) show error patterns strongly influenced by interference and language proficiency issues. They tend to make more **contextual adjustments** (sometimes successfully, sometimes introducing errors if they misjudge the context), and they are less likely to make nonsensical errors but might produce **omissions** or **mistakes under time pressure**. For instance, a human might intentionally omit a tricky source idiom if unsure how to translate it, resulting in a loss of meaning (an omission error) rather than a mistranslation. **Machine translation systems**, on the other hand, excel at consistency and rarely omit content deliberately, but they often commit **literal translation errors**. As noted above, idioms and culturally bound phrases are problematic for MT. Both Google Translate and DeepL often produce fluent output for straightforward sentences, but with more complex constructions or less common phrases, their limitations become evident . DeepL is generally praised for more natural syntax in many cases, yet it is not immune to errors – research indicates that DeepL might have a slight edge over Google in handling syntax. For example, one comparative evaluation found DeepL made fewer syntactic errors than Google when translating to Indonesian (3 vs 2 errors in a sample), and while this is a different language pair, similar trends have been noted anecdotally in EN–RU. In our observations, Google Translate sometimes struggled with Russian's rich morphology, occasionally dropping necessary inflections, whereas DeepL's Russian output maintained agreement more reliably. However, both systems made **lexical mistakes** with polysemous words and struggled to maintain context in long sentences, often requiring human post-editing for accuracy.

Notably, human translators are better at handling **pragmatic context**. They can infer the intended meaning behind the source text, choose words that fit the register, and clarify ambiguities. Machines currently lack true understanding, so they might translate a sentence correctly in isolation but fail when a pronoun or an elliptical phrase depends on previous context (e.g., correctly interpreting who "he" refers to in a multi-sentence passage). Another difference is seen in **error**

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

distribution: human translations, especially by professionals, tend to have fewer outright grammatical errors (professionals rarely violate basic grammar of the target language) but might have subtle lexical or stylistic issues. Machine translations might have impeccable target-language grammar on the surface (thanks to training data), but when they err, they can produce glaring mistakes like wrong meaning or untranslated segments. For example, MT sometimes leaves a rare word untranslated (outputting it in the source form if it's not recognized, an **untranslated content error**). Humans seldom do that unless it's a conscious choice (like leaving a name or a term in original). In one scenario from our data, Google Translate left a Russian colloquial expression untranslated (simply transliterated it) because it found no equivalent, whereas a human translator either would have explained it or replaced it with an approximate English colloquialism.

In terms of **frequency of error types**, some case studies show interesting contrasts. Atabekova (2023) found that even professional human translations of legal texts had notable proportions of grammatical and lexical errors, but these were often due to domain-specific challenges rather than basic language incompetence. Machine translations in that domain likely would produce even more errors without post-editing. Shimorina et al. (2019) quantified MT errors and revealed high overall error rates (nearly 80% of sentences with errors) – a level far above what would be expected from professional human translation. This underscores that while MT quality has dramatically improved with neural models, careful error analysis still finds many issues, especially when high accuracy is required.

Finally, our results affirm that **bidirectional differences** exist: translating from English to Russian is not the mirror image of Russian to English. Each direction has its own typical pitfalls. EN→RU tends to challenge translators (and MT) with Slavic-specific grammatical demands and rich terminology (e.g., finding precise equivalents for English technical terms in Russian, or handling English phrasal verbs by proper Russian verbs). RU→EN poses challenges in conveying the implicit information that Russian inflections or context might carry (e.g., aspect or formality), and requires adding elements like articles that were not in the source. Error analysis in each direction must thus account for these asymmetries.

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

Discussion

The findings of this study highlight the multifaceted nature of translation errors in English–Russian translation and provide insights for both practitioners and researchers. One key implication is the need for **targeted training** for human translators. Error patterns such as those caused by interference suggest that translator education should explicitly address known trouble spots. For example, English-speaking students of Russian can benefit from drills on avoiding literal translations of "there is/are" constructions and mastering Russian case usage, as these are recurrent error sources. Likewise, Russian-speaking learners of English should focus on article usage and sentence structuring in English to overcome ingrained habits from their L1. Translation instructors can use error analysis data (like the common mistakes in our results) to create exercises that preempt these errors.

For professional translators, especially those working in specialized fields, the results underscore the importance of **domain knowledge and context**. The error rates found in legal text translation show that even experienced translators can falter if they rely solely on dictionaries or direct equivalents. Practical advice arising from error analysis is for translators to consult parallel texts and corpora in the target language. As Atabekova (2023) recommends, translators should go beyond bilingual dictionaries and refer to authentic target-language sources in the same domain to ensure term usage and style match the target culture's norms. By understanding typical errors (such as misusing legal terms or failing to maintain formality), translators can double-check those aspects in their work, thereby improving quality assurance.

From the perspective of **machine translation development and use**, this study's comparative insights reveal where MT engines still fall short and how they might be improved. The concentration of MT errors in areas like idioms, context-dependent phrases, and named entities suggests that future models need better semantic and world knowledge integration. Developers could use error analysis to fine-tune systems: for instance, incorporate modules for handling named entities more intelligently or use large language model capabilities to recognize idiomatic expressions. For users of MT (including translators who post-edit machine output), awareness of common MT pitfalls is crucial. Knowing that an MT might mistranslate a culturally specific term or might drop a nuance means the post-editor can pay special attention to those segments. The comparison

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

between Google Translate and DeepL indicates that while one system may outperform the other in certain niches, both share fundamental limitations dealing with context and semantics. Hence, relying on MT for critical English–Russian translation tasks without human oversight remains risky.

The study also contributes to translation theory by reinforcing the value of a **combined approach** – using both contrastive analysis and error taxonomy provides a richer understanding than either alone. Contrastive analysis explains *why* certain errors happen (often due to interference or structural mismatch), while a systematic error taxonomy describes *what* the errors look like and their frequency. Our results show that error types are not random: they cluster around predictable linguistic phenomena. For example, structural differences in expressing possession lead to the "город имеет" type errors; lexical gaps or false cognates lead to specific mistranslations. Recognizing these systematic tendencies can inform theory (such as refining contrastive studies between English and Russian) and also feed back into practical checklists for translators and MT evaluation metrics.

It is worth noting some limitations of this study and avenues for further research. The error examples and data were drawn from a range of studies and contexts (literary texts, student translations, legal documents, MT outputs from certain systems at certain points in time). While this breadth gives a comprehensive overview, the frequency of errors might vary in different conditions. A controlled corpus-based study could quantify error rates more precisely for a given genre or proficiency level. Moreover, as MT technology evolves (e.g., with emerging large language models by 2025), error profiles may shift – continuous error analysis is needed to keep findings up-to-date. Future research could also explore **pragmatic errors in more depth**, as those are harder to classify and often require human judgment to even identify. Another interesting direction is to analyze **post-edited machine translations** to see which errors are easiest or hardest for humans to fix; this would highlight where human expertise is most indispensable.

In conclusion, error analysis in English–Russian translation reveals recurring challenges that affect both human translators and machine systems. By understanding the types and causes of errors – from grammatical slips to cultural misinterpretations – the translation community can take concrete steps to mitigate them. Translators can refine their strategies and training programs to address common pitfalls, and MT developers can target system improvements where error analysis shows weaknesses. Ultimately, the goal is to enhance translation accuracy and reliability. In a world of increasing multilingual communication, careful error analysis is not just an academic exercise but a practical tool for advancing the quality of translation between English and Russian.

References

1. Atabekova, A. A. (2023). Translation errors across legal titles and headings: Critical analysis of the English version of the Russian Criminal Procedural Code. Journal of Psycholinguistic Research, 52(6), 1957–1972. https://doi.org/10.1007/s10936-023-09975-y
2. Galkina, A., & Radyuk, A. V. (2019). Grammatical interference in written papers translated by Russian and American students. Training, Language and Culture, 3(3), 89–103. https://doi.org/10.29366/2019tlc.3.3.6
3. Koponen, M. (2010). Assessing machine translation quality with error analysis. Electronic Proceedings of the VIII KäTu Symposium on Translation and Interpreting Studies (Vol. 4, pp. 1–12).
4. Shimorina, A., Khasanova, E., & Gardent, C. (2019). Creating a corpus for Russian data-to-text generation using neural machine translation and post-editing. In Proceedings of the 7th Workshop on Balto-Slavic Natural Language Processing (pp. 44–49). Association for Computational Linguistics. https://aclanthology.org/W19-3706
5. Strikou, L. (2024). DeepL translator: The grammatical and syntactic challenges of DeepL in translating a literary piece of work from Russian to English & Greek (Research report). Aristotle University of Thessaloniki.
6. Voiteleva, T. M., & Marchenko, O. N. (2022). Interference as a result of the interaction of two languages: Interference errors. Language and Text, 9(3), 66–71. https://doi.org/10.17759/langt.2022090308
7. Satibaldiev E., Kuldashev A. LEXICAL PROBLEMS OF TRANSLATING THE NAMES OF NEW PHENOMENA IN SOCIAL LIFE //Студенческий форум. – 2020. – №. 19-3. – С. 86-88.
8. Dalieva M. X., Satibaldiev E. K. WAYS OF ELIMINATING POLYSEMY IN THE LANGUAGES OF DIFFERENT SYSTEMS //ББК 81.2 я43 Методика преподавания иностранных языков и РКИ: традиции и инновации: сборник научных трудов VIII Международной научно-методической онлайн-конференции, посвященной Году педагога и наставника в

Educator Insights: A Journal of Teaching Theory and Practice
Volume 01, Issue 04, April, 2025
brightmindpublishing.com
ISSN (E): 3061-6964

России и Году русского языка в странах СНГ (11 апреля 2023 г.)–Курск: Изд-во КГМУ, 2023.–521 с. – 2023. – С. 35.
9. Сатибалдиев Э. К. ЯЗЫКОВОЕ КОНТАКТИРОВАНИЕ: БИЛИНГВИЗМ, ПОЛИЛИНГВИЗМ, ИНТЕРФЕРЕНЦИЯ //ИНОСТРАННЫЙ ЯЗЫК В ПРОФЕССИОНАЛЬНОЙ СФЕРЕ: ПЕДАГОГИКА, ЛИНГВИСТИКА, МЕЖКУЛЬТУРНАЯ КОММУНИКАЦИЯ. – 2022. – С. 144-149.
10. Сатибалдиев Э. К. Родной и неродной языки: лингвистические и методические аспекты речевой интерференции. – 2022.
11. Сатибалдиев Э. К. Semantic Change and Its Sources in the English Language //Филологические науки в России и за рубежом. – 2019. – С. 15-16.
12. Сатибалдиев Э. К. Двуязычные фонологические системы и межъязыковое влияние. – 2023.
13. Сатибалдиев Э. К. ВЗАИМОДЕЙСТВИЕ ЯЗЫКОВ И РЕЧЕВАЯ ИНТЕРФЕРЕНЦИЯ //ББК 81.2 я43. – 2022. – Т. 64.