# PROBLEMS IN THE MACHINE TRANSLATION OF ECONOMIC TERMS AND CONCEPTS FOR OVERCOMING THEM

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**Abstract:** *In the era of globalization, the accurate translation of economic terminology has become essential for effective international communication in trade, finance, and investment. This study investigates the challenges associated with the machine translation of economic terms and proposes strategies for overcoming them. The research explores the linguistic and functional characteristics of economic terminology and evaluates the performance of various machine translation paradigms, including Rule-Based Machine Translation (RBMT), Statistical Machine Translation (SMT), Neural Machine Translation (NMT), and Large Language Model (LLM)-based systems.*

**Keywords**: *economic terminology, machine translation, SMT, NMT, large language models, terminology management, post-editing, standardization, Uzbek language.*

**Introduction:** Because globalization is getting stronger, trade, financial, and economic ties between countries are growing a lot. This process makes it even more important to use the right economic terms and communicate well on an international level. Economic terms help to clearly, concisely, and unambiguously express specific domain concepts. They are also an important way to share scientific and practical knowledge. The precision and uniformity of terminology guarantee the proper interpretation of economic data; otherwise, erroneous translation may result in significant mistakes in economic decision-making (Cabré, 1999; Temmerman, 2000). In the context of globalization, economic terminology is one of the most important parts of working together internationally. The growth of international trade, banking and finance, investment, and the digital economy needs quick and accurate sharing of economic information across languages. Consequently, translating economic terminology while taking into account their linguistic and cultural characteristics has emerged as a significant scientific and practical endeavor. To fully understand economic texts, it is important to use consistent terminology and conceptual equivalence. This means that specialized methods must be used in the translation process (Bowker & Pearson, 2002). As modern information technologies have advanced, machine translation (MT) has become an important tool for translating economic texts. Statistical Machine Translation (SMT), Neural Machine Translation (NMT), and Large Language Models (LLM) are all types of systems that can quickly translate a lot of text. This greatly speeds up cooperation in business and science between countries. The polysemy of economic terms, their contextual dependency, and their specificity to national economic systems pose significant challenges in machine translation. Consequently, examining the efficacy of machine translation systems in handling economic terminology constitutes a

pertinent scientific inquiry (Koehn, 2020; Hutchins & Somers, 1992). The objective of this study is to ascertain the challenges faced in the machine translation of economic terminology and to formulate effective strategies for their resolution. To attain this objective, various tasks are delineated: analyzing the linguistic and functional characteristics of economic terminology; evaluating the strengths and weaknesses of machine translation systems in rendering economic texts; identifying and categorizing terminological inaccuracies; and formulating pragmatic recommendations to mitigate them. The research focuses on the machine translation process of economic texts, specifically examining the linguistic, semantic, and terminological challenges encountered in the translation of economic terminology. This method helps to make the study's goals clear and make sure that the scientific results are consistent (Williams & Chesterman, 2002). The study utilizes various methodological approaches. Comparative analysis is employed to evaluate the outputs of human and machine translation; corpus analysis investigates the frequency and contextual attributes of economic terminology in authentic texts; and terminological analysis delineates the semantic structure, equivalence, and level of standardization of terms. Additionally, descriptive and functional methodologies are crucial for validating the reliability of research findings (Baker, 1993; Bowker & Pearson, 2002).

**2. Theoretical Underpinnings** 2.1. The Idea of Economic Terms and What They Are Economic terminology is an important part of scientific communication because it is a system of words that convey specialized knowledge. A term is generally defined as a lexical unit that expresses a specific concept within a particular scientific or professional field, characterized by a restricted meaning and relatively low context dependency. Terms are important for organizing, storing, and sharing scientific knowledge, and they make sure that communication is clear (Cabré, 1999). Economic terms convey ideas associated with economics, finance, banking, taxation, and investment activities, facilitating efficient information exchange in these domains (Bowker & Pearson, 2002). The distinctions between terms and general vocabulary are distinctly evident in their functional and semantic characteristics. General vocabulary is used a lot in everyday conversation, and it is often characterized by polysemy, emotional expressiveness, and context dependency. Terms, on the other hand, are meant to describe a certain idea, so their main characteristics are accuracy, systematicity, neutrality, and monosemy (Temmerman, 2000). For instance, words like inflation, liquidity, and gross domestic product have very specific meanings when used in economics, and their meanings are more stable than those of general vocabulary. There are many ways to group economic terms based on what they mean and how they are used. One of the most common ways to group them is by their functional areas. Financial terms like "revenue," "expenditure," "assets," and "liabilities" talk about how businesses and governments handle money. Banking terms like "interest rate," "deposit," "loan," and "collateral" talk about how banks work. Tax terms like "value-added tax," "income tax," and "tax liability" talk about how the government handles money. Finally, investment terms like "portfolio," "dividend," "equity," and "bond" talk

about how to invest money and how the stock market works. This kind of classification is important for putting together systems of terms and finding the right equivalents in translation (Sager, 1990). One of the main problems with terminology has to do with monosemy, polysemy, and standardization. Theoretically, terms gravitate towards monosemy due to the necessity of precision and clarity in scientific communication (Wüster, 1979). In practice, though, many economic terms have more than one meaning. In accounting, equity might mean "owner's capital," but in financial markets, it might mean "shares." In the same way, the word "margin" can mean different things depending on the situation. This requires contextual analysis in both human and machine translation (Temmerman, 2000). Standardization is a very important part of making sure that terms are used in the same way. It makes sure that terms are used in the same way and with the same meaning, which helps communication between countries. International organizations like ISO come up with rules for how to use terms to make sure they are clear and consistent (ISO 704, 2009). Standardization is very important for MT systems because termbases and glossaries make translations much better (Bowker, 2015).

2.2. Progress in Machine Translation Technologies Machine Translation (MT) technologies have been very helpful in breaking down language barriers and speeding up communication between countries. There are several steps in the development of translation systems: Rule-Based Machine Translation (RBMT), Statistical Machine Translation (SMT), Neural Machine Translation (NMT), and modern systems based on Large Language Models (LLMs). Each method has its own theoretical basis, technological strengths and weaknesses, and levels of success when it comes to translating economic terms. One of the oldest and most common types of machine translation is rule-based machine translation (RBMT). This method uses language rules, grammar-based dictionaries, and bilingual databases of terms. In RBMT systems, the translation process goes through steps of morphological, syntactic, and semantic analysis. This method works well for making sure that terms are correct, especially when translating standardized economic terms, where it makes things very consistent. However, RBMT systems have some problems. They need a lot of language resources, aren't very flexible, and have trouble translating idioms (Hutchins & Somers, 1992; Arnold et al., 1994). Statistical Machine Translation (SMT) has been widely used since the 1990s. It uses large parallel corpora to make probabilistic models that do the translation. By finding statistical similarities between segments in the source and target languages, SMT systems choose the most likely translation. This method is more adaptable than RBMT and gives results that are more like how people actually use language. However, SMT systems frequently exhibit grammatical inconsistencies, fail to address long-distance dependencies, and demonstrate diminished terminological precision (Koehn, 2010). The fact that economic terms can mean more than one thing could cause SMT systems to choose the wrong equivalents. Over the past ten years, Neural Machine Translation (NMT) has made a big difference in machine translation. This method is based on artificial neural networks, especially the encoder-decoder

structure and attention mechanisms. NMT systems can look at the context of the text, which makes the translation much better (Bahdanau et al., 2015). The addition of transformer architecture has made things even more efficient (Vaswani et al., 2017). NMT systems offer natural and fluent translations of economic texts; however, they are plagued by challenges including insufficient data for low-resource languages, sporadic disruptions in terminological consistency, and the phenomenon of "hallucination," which refers to the generation of non-existent information (Koehn, 2020).

Translation systems that use Large Language Models (LLMs) have reached a new level of development in the field of machine translation in the last few years. These models have been trained on huge multilingual datasets and can really understand context, make sure that the meanings are the same, and make sure that the terms are consistent. LLMs, especially those that use transformer architecture, look at more than just literal equivalence. They also look at pragmatic and discourse-level features (Brown et al., 2020). This is very important for making sure that economic terms are translated correctly and in a way that makes sense in the context. But LLM-based systems need a lot of computing power, may need more control systems to keep terminology consistent, and may cause problems with data reliability. In general, each step in the development of machine translation technology has its own pros and cons. RBMT guarantees terminological precision and manageability, SMT provides adaptability through extensive datasets, NMT enhances contextual comprehension and fluency, whereas LLM-based systems are distinguished by semantic profundity and versatility. Consequently, the amalgamation of these methodologies may yield the most efficacious outcomes in the translation of economic terminology.

2.3. The Function of Economic Terminology in Translation Studies Economic terminology is a crucial aspect of translation studies, as it facilitates the precise and uniform conveyance of specialized knowledge into different languages. Choosing the right words during the translation process not only keeps the meaning of the text, but also fully conveys its functional and practical aspects. Financial reports, banking documents, investment agreements, and economic analyses are all examples of economic texts that need to be very accurate. Consequently, terminological consistency and conceptual equivalence are principal criteria for translation quality (Newmark, 1988; Cabré, 1999). Terminological equivalence is a key idea in translating words and phrases used in economics. It describes how a word in the source language and its equivalent in the target language are similar in meaning, function, and idea. In translation studies, there are three types of equivalence: full equivalence, partial equivalence, and non-equivalence. For example, "inflation" means the same thing in both languages, so "inflation" means the same thing in both languages. Partial equivalence happens when the meaning or scope of a word doesn't match exactly. For example, the word "equity" can mean "owner's capital" or "shares," depending on the situation. When there isn't an equivalent term in the target language, strategies like descriptive translation, transliteration, or making up new terms are used (Baker, 2018; Pym, 2014). Standardization and unification processes in economic terminology are

crucial for maintaining consistency in translation. Standardization seeks to guarantee that terms are employed in a consistent form and meaning, thereby averting misunderstandings in global communication. Unification means putting different versions of the same idea together according to one standard. ISO and other international standardization groups have come up with rules for how to use terms so that they are correct, consistent, and fit together (ISO 704, 2009). Using standardized terms in business, especially in banking and finance, makes legal and financial documents more reliable and cuts down on translation mistakes (Sager, 1990). Termbases and glossaries are important tools for keeping track of economic terms and making translations better. A termbase is a well-organized set of information about terms that are used in a certain field, such as their meanings, synonyms, and how they are used. A glossary, on the other hand, is a list of words that are used in a certain text or project. These resources make sure that terms are used consistently and are useful for both translators and machine translation systems (Bowker & Pearson, 2002). The integration of termbases into modern translation technologies, especially Computer-Assisted Translation (CAT) tools, makes translation much faster and less likely to go wrong (Bowker, 2015). Also, terminological resources are very important for making machine translation systems better. The level of accuracy and consistency in terminology goes up a lot when neural machine translation and LLM-based systems are used with termbases. This guarantees the professional translation of economic texts and improves the efficiency of international economic collaboration (Koehn, 2020). To sum up, economic terms are very important in the study of translation. To make sure that economic texts are translated well, it is important to use termbases and glossaries correctly, to have standardization and unification processes, and to have terminological equivalence. These things are important not only for human translation but also for making machine translation systems work better in both theory and practice.

**3. Issues Faced in the Machine Translation of Economic Terminology** 3.1. Lexical-Semantic Issues One of the biggest problems with machine translation (MT) of economic terms has to do with lexical-semantic features. Even though terms in economics are often clear and consistent, their polysemy, synonymy, variability, the problem of false friends, and context-dependence can make translation hard. These problems have a direct impact on how well machine translation systems can guarantee semantic equivalence and terminological accuracy (Baker, 2018; Koehn, 2020). Polysemy, or having multiple meanings, is an important part of economic language. It happens when one word has different meanings in different situations. Theoretically, terms tend toward monosemy; however, in practice, numerous economic terms may possess multiple semantic interpretations (Cabré, 1999). In accounting, the English word "equity" means "owner's capital," while in financial markets, it means "shares." The word "margin" can also mean "profit margin," "collateral amount," or "boundary." When machine translation systems don't take context into account well enough, they might choose the wrong equivalents, which can change the meaning of economic texts (Temmerman, 2000). Synonymy and variation are also important problems when

translating economic terms. Having more than one word to describe the same idea can make it hard to keep terminology consistent. The English words revenue, income, and earnings may mean the same thing in some situations, but they are used and understood differently. In Uzbek, daromad, tushum, or foyda may be used to mean these. Machine translation systems don't always get these small differences right, which leads to inconsistent terminology (Bowker & Pearson, 2002). Using different forms of a word, which is called variation, makes translation harder. Value-added tax (VAT) and consumption tax are two examples of taxes that are similar but may be used in different situations.

Another common cause of mistakes in machine translation is the phenomenon of false friends. These are words that look the same but mean different things. When translating from English or other European languages into Uzbek, these kinds of units can be especially difficult. The English word "actual" means "real," but it is often wrongly translated as "aktual." Also, the word "commodity" means "goods," but it can also be spelled "kommoditet," which can be confusing. Because machine translation systems use statistical or neural models, they might choose the wrong translations based on these similarities (Baker, 2018). Context-dependence is a key factor in accurately translating economic terms. A lot of words only have certain meanings in a certain conversation or field. In an economic sense, "capital" means "capital," but in other contexts, it can mean "city" or "uppercase letter." Interest can also mean "interest rate" or "curiosity." Machine translation systems have a hard time figuring out these kinds of semantic differences, especially when they are working with short texts or not enough context (Koehn, 2020). Even though NMT and LLM-based systems can look at context more deeply, they need to be able to use other terminology resources to be sure they are correct. So, lexical-semantic problems like polysemy, synonymy and variation, false friends, and context-dependence are some of the biggest problems that machine translation of economic terms faces. To deal with these problems, we need to use terminological databases, do better contextual analysis, and get domain experts involved. This helps make translations better and makes sure that international communication is clear. 3.2. Issues with Morphology and Syntax

Problems with machine translation of economic terms aren't just about words and meanings; they also have to do with how words are formed and how they fit together in sentences. The translation process is made much harder by the fact that languages with different typological structures are different from each other. English is an analytic language, which means that it uses word order and auxiliary words to show grammatical relationships. Uzbek, on the other hand, is an agglutinative language, which means that it uses many suffixes to show grammatical meanings. These dissimilarities pose significant challenges for machine translation systems and impact the precise and uniform translation of economic terminology (Baker, 2018; Koehn, 2020).In agglutinative languages like Uzbek, you can add grammatical suffixes to words to show complicated meanings and syntactic relationships. For instance, the English word "investment" can be translated into Uzbek as investitsiya, investitsiyalar,

investitsiyalarning, investitsiyalarga, investitsiyalardan, and so on. Machine translation systems, particularly those trained on restricted datasets, frequently encounter difficulties in accurately analyzing and generating these forms. Consequently, grammatical errors, erroneous case endings, or numerical discrepancies may arise, adversely impacting terminological precision and diminishing the text's professional quality (Sager, 1990; Temmerman, 2000).Another important problem is that the order of the words is different. The structure of English is usually SVO (Subject–Verb–Object), while the structure of Uzbek is SOV (Subject–Object–Verb). For instance, "The company increased its capital" is translated as "Kompaniya o'z kapitalini oshirdi." Machine translation systems don't always get these kinds of differences right, especially in long sentences or those with more than one modifier. This can lead to translations that sound strange or are grammatically wrong (Newmark, 1988; Koehn, 2020).

There are also problems with abbreviations and acronyms in economic language. In conversations about the world economy, people often use short forms like GDP (Gross Domestic Product), VAT (Value-Added Tax), and ROI (Return on Investment). Instead of being translated directly, these are often replaced with words that mean the same thing in the target language: GDP = YAIM, VAT = QQS, and ROI = Investment profitability. Machine translation systems might get these abbreviations wrong, leave them out, or add to them in the wrong way, which makes things less clear and consistent (Bowker & Pearson, 2002).

Also, some abbreviations can mean different things depending on the situation, which makes it even more important to look at the context. ROI can mean different things in marketing, finance, and investment analysis, for example. Integrating terminology databases and glossaries is necessary for precise interpretation (Koehn, 2020).

In conclusion, the main problems with machine translation are suffixation in agglutinative languages, differences in word order, and abbreviations. To deal with these, we need more advanced neural models, combining terminology resources, and thinking more deeply about language features.3.3. Issues with culture and pragmatics. Pragmatic and cultural issues are among the most complex aspects of translating economic terms in machine translation. These issues pertain not only to linguistic equivalence but also to the accurate interpretation of the social, cultural, and institutional context of the text. Economic texts frequently embody the economic system, legal standards, and institutional framework of a particular nation, necessitating the consideration of conceptual systems alongside linguistic units (Chesterman, 2016; Newmark, 1988). Ideas that are unique to national economic systems are very hard to deal with. Every country has its own way of doing business and its own words, which may not have direct translations in other languages. In Uzbek, there are no direct equivalents for terms like "Social Security tax" (USA) or "Council Tax" (UK). Machine translation systems frequently depend on literal translation, which can alter meaning (Baker, 2018). There are also problems because of differences in laws and institutions. The meanings of words like "LLC," "PLC," and "corporation" differ from

one legal system to the next. If you don't take these differences into account, you could end up with wrong translations that change the legal and economic meaning (Šarčević, 1997). Another important issue is localization. This means changing texts to fit the cultural, economic, and legal context of the people who will read them, such as how numbers are written, what currency is used, and what institutional terms are used. For instance, "1 billion" can be translated as "1 milliard dollar," but the word "billion" can mean different things to different people. Not localizing correctly can cause confusion (Esselink, 2000). Some economic terms, like "welfare state" or "free market economy," are also loaded with cultural meaning because they have ideological meanings. Machine translation systems frequently do not accurately convey these subtleties, resulting in oversimplification or misinterpretation (House, 2015). In conclusion, national-specific concepts, legal disparities, and localization challenges constitute significant pragmatic and cultural impediments. To deal with them, we need adaptive systems that take culture into account.

3.4. Issues with Technology Problems with machine translation technology are closely linked to system architecture, training data, and the availability of resources. Even though NMT and LLMs have come a long way, they still rely heavily on the quality, quantity, and domain-specific resources of the data (Koehn, 2020; Koehn & Knowles, 2017). A big problem is that there aren't enough parallel corpora, which are sets of texts in different languages that are used to train MT systems. In the economic field, there aren't many of these kinds of corpora, so systems have to use general data, which makes them less accurate (Bojar et al., 2016). Another issue is that the same word is translated differently in different parts of a text. For instance, equity might be called "capital" in one case and "shares" in another. This lowers the level of professionalism (Koehn, 2020; Castilho et al., 2017). Uzbek and other low-resource languages also have performance problems because they don't have enough data. Transfer learning is useful, but it doesn't yet give perfect results (Aharoni et al., 2019). Lastly, not being able to handle enough context is still a problem. Even advanced systems have trouble with long texts, which can lead to different interpretations. For example, in the same text, "capital" can mean both "capital" and "city" (Vaswani et al., 2017; Koehn, 2020). In conclusion, the main technological problems are the lack of parallel corpora, inconsistency, low-resource challenges, and limited context handling. To deal with them, we need to grow domain-specific corpora, combine terminology systems, and make models that are more aware of the context.

**4. Ideas for solving the problems** 4.1. Making databases and glossaries of terms One of the best ways to fix problems that come up when translating economic terms is to make terminological databases and glossaries in a systematic way and use them in the translation process. Terminological resources help to standardize units that are specific to a certain field, make sure they always have the same form and meaning, and keep things consistent during translation. This method is very important in fields where accuracy is very important, like economic texts, and it makes machine translation systems much better (Bowker, 2015; Cabré, 1999). One of the best ways to keep track of

economic terms is to create specialized termbases for each field. A termbase is a well-organized set of data that includes terms from a certain field, their definitions, grammatical features, how they are used in context, and how they are used in other languages. In economics, these kinds of databases give exact and standardized translations of words like inflation, liquidity, equity, and gross domestic product. This lessens the inconsistency of terms and makes machine translation systems more semantically accurate (Sager, 1990; ISO 704, 2009). Also, terminological databases should be kept up to date all the time because economic systems and financial terms are always changing. Glossaries, on the other hand, are usually short lists of words that are used in a certain project, text, or corpus. Glossaries are more useful and focused on context than termbases. They are quick reference tools for translators or machine translation systems. Glossaries help keep stylistic and terminological consistency when translating economic texts by making sure that terms are used the same way throughout the document. This is especially important in documents with many authors or that are very big (Bowker & Pearson, 2002). Translation Memory (TM) systems are also very important for machine translation and computer-assisted translation (CAT) tools. TM systems keep sentences and segments that have already been translated and use them again in future translations. This method speeds up the translation process and makes sure that the terms are always the same. TM systems work especially well in economic texts that have a lot of repeated structures, like contracts, financial reports, and banking documents (Somers, 2003). Also, combining terminological databases with TM systems makes modern neural machine translation and CAT tools work better. This integration means that systems don't just use statistical or neural models; they also use validated terminological resources. This leads to fewer wrong translations of economic terms and a better overall quality of the text (Koehn, 2020). To sum up, making databases and glossaries of terms and using translation memory systems are some of the best ways to make machine translation of economic terms less problematic. These methods make sure that information is accurate, consistent, and standardized, which makes international economic communication better. 4.2. Approaches Based on Artificial Intelligence Artificial intelligence (AI)-based approaches are very important for solving problems in the machine translation of economic terms. Modern translation systems use more than just linguistic rules and statistical models. They also use large language models and neural networks that have been trained very well. These technologies make sure that the translation process is consistent, improve contextual understanding, and make sure that the terms are used correctly (Koehn, 2020; Vaswani et al., 2017). TMS, or terminology management systems, are important parts of the AI-based translation ecosystem. These systems keep track of terms in central databases, keep track of their equivalents, and use them automatically when translating. In the field of economics, TMS makes sure that terms like inflation, equity, liquidity, and asset are translated in a consistent and standardized way. This cuts down on inconsistencies and makes the text better (Bowker, 2015; ISO 704, 2009). Another good way to improve things is to fine-tune Neural Machine Translation (NMT) and Large Language Models

(LLMs). During this process, general models are trained again using data that is specific to a field, like texts about economics or finance. This helps models better understand and translate specialized terms correctly. As a result, the precision of intricate and polysemous economic terminology markedly enhances (Devlin et al., 2019; Koehn, 2020). But this process needs high-quality domain-specific corpora; if not, problems like overfitting or poor generalization could happen. One of the most important things that AI-based systems have done is make context-sensitive translation systems. These systems look at text not just at the sentence level, but also at the paragraph or discourse level. This makes sure that economic terms are translated in a way that makes sense in context. For instance, the word "capital" is understood correctly based on the situation. Transformer-based models are especially good at dealing with these kinds of dependencies (Vaswani et al., 2017). But keeping the global context and consistency in very long texts is still hard. AI-based systems can also use adaptive learning, which lets them improve the quality of translations based on user corrections. This feature is very important for translating business documents because the language used in business and law changes all the time. Adaptive systems can change how they translate in real time and keep the same level of quality (Castilho et al., 2017). To sum up, some of the best AI-based ways to deal with problems with translating economic terms are terminology management systems, fine-tuning NMT and LLM models, and context-sensitive translation systems. These technologies make translations better, make sure they are consistent, and make it easier for people to talk about business across borders.

4.3. Making things the same and bringing them together Standardization and unification are very important for making sure that machine translation of economic terms is correct and consistent. Standardization seeks to guarantee that terms are utilized in a consistent form and meaning, thereby minimizing communicative discrepancies among languages and economic systems. Unification means putting all the different ways of saying the same thing into one standard form. To make translations more consistent and better, both processes are necessary (Sager, 1990; Bowker, 2015). The International Organization for Standardization (ISO) is responsible for creating the main theoretical and practical framework for standardizing economic language. The ISO 704 standard talks about important ideas for working with terms, such as how to define concepts, choose terms, and stay consistent (ISO 704, 2009). These standards help make sure that terms like inflation, liquidity, asset, and liability are used the same way in all languages. This makes the terms more stable and makes machine translation less likely to make mistakes.Standardization should also be done on a national level. Each country should make its own rules about how to use terms that fit with its economy, since what works in one country may not work in all countries. Tax systems, banking practices, and financial reporting terminology may vary among nations. So, national terminological policies help make sure that terms are used in the same way everywhere (Cabré, 1999; Temmerman, 2000).This is especially important for languages with few resources, like Uzbek. Making standardized economic terms better for machine translation and less likely to be wrong. Termbases, national glossaries, and corpus linguistics can all be used

to make sure that policies are both linguistically and conceptually correct (Bowker & Pearson, 2002).Also, combining standardization and unification processes with machine translation and AI systems gives even better results. Adding ISO-based terminology resources to NMT and LLM models makes it possible to use terms correctly and consistently, which greatly improves translation quality and cuts down on the need for human intervention (Koehn, 2020).In conclusion, the main ideas for solving translation problems are to make terminology consistent across countries and to create national terminology policies. These methods make sure things are the same, make things better, and make it easier for people all over the world to talk about business.4.4. Working together with machines (Human-in-the-loop)Human–machine collaboration (Human-in-the-loop) is very important for dealing with the difficulties of translating economic terms. This method does not fully automate the translation process; instead, human translators check and improve machine-generated translations. This model is very important in fields where accuracy is very important, like economics, law, and finance. It helps cut down on mistakes in terminology and make sure that the meaning is correct (O'Brien, 2012; Koehn, 2020).Post-editing is the process by which human translators fix and improve text that has been translated by a machine. Translators look over the grammar, vocabulary, and style and make any changes that are needed. Post-editing is necessary in economic texts to make sure that terms are used correctly, since machine translation can get polysemous terms wrong or pick equivalents that don't fit the context. Post-editing can be light or full, depending on what you need it for and how good the work needs to be (TAUS, 2010; O'Brien, 2012).Professional translators are an important part of this method. Even though modern NMT and LLM systems work very well, they can't fully understand the subtleties of context, the meanings of pragmatics, and the realities of the economy in different countries. So, human translators are not only experts in languages, but also in their fields. They make sure that terms are used correctly, check for equivalence, and come up with new ways to use terms when needed (Newmark, 1988; Pym, 2014).The hybrid translation method uses both machine and human translation. In this model, the MT system makes a first translation, which a human translator then improves. This method strikes a good balance between speed and quality, especially when translating big economic documents like financial reports, banking documents, and international contracts (Somers, 2003; Koehn, 2020).Also, human-in-the-loop systems can include ways for the system to keep learning, like when people make changes and send them back to the system for retraining. This improves the model's accuracy and adaptability over time. This is especially important in fields that are always changing, like economics, where new words and ideas are always coming up (Castilho et al., 2017).In conclusion, post-editing, the active participation of expert translators, and hybrid translation methodologies represent some of the most effective human-machine collaboration frameworks for resolving issues in the machine translation of economic terminology. These methods make translations better, make sure that terms are used correctly, and make it easier for people from different countries to talk about business.

**5. Real-World Analysis**This section presents a comparative study utilizing a selected corpus to empirically examine the challenges faced in the machine translation of economic texts. The study utilizes a compact parallel corpus comprising international economic reports, banking documents, and investment-related texts. Because these kinds of texts need a lot of accuracy in their terminology, they are good for testing how well machine translation systems really work (Koehn, 2020; Bowker & Pearson, 2002).The analysis compares the translation outputs of different machine translation systems, such as Google Translate, DeepL, and ChatGPT. These systems use modern neural machine translation and large language models, but they are built and optimized in different ways. Google Translate uses large-scale parallel corpora to make sure that translations are of good quality for general use. DeepL, on the other hand, focuses more on naturalness and stylistic accuracy. On the other hand, ChatGPT is known for its ability to better ensure understanding of the context and coherence at the discourse level (Vaswani et al., 2017; Koehn, 2020).The comparative analysis shows that there are a number of mistakes in the translation of economic terms. There are three main types of these mistakes: lexical-semantic, morphological, and pragmatic. For instance, common problems include translating polysemous words incorrectly in the wrong context (for example, translating "capital" as "city" instead of "capital"), adding or leaving out abbreviations incorrectly (for example, not explaining GDP), and using synonyms inconsistently (for example, translating "revenue" as "income" in one case and "earnings" in another) (Baker, 2018). Statistical analysis classifies the errors into four main groups: lexical errors, terminological errors, grammatical errors, and contextual errors. The results show that the most common type of error is a terminological error. This is because there aren't many domain-specific terminological resources for economic texts. NMT- and LLM-based systems usually make outputs that are grammatically correct, but they don't always use the same terms (Castilho et al., 2017). When looking at how well the proposed solutions work, the effect of combining terminological databases, glossaries, and post-editing is looked at. The results of experiments show that machine translation systems work better when they are used with specialized economic termbases. In particular, the number of terminological inconsistencies and synonymic confusion goes down, and the text as a whole becomes more accurate. Furthermore, the use of post-editing greatly improves the quality of the final translation, which shows that the human-in-the-loop method works in practice (O'Brien, 2012; Bowker, 2015).

The practical analysis shows that even though modern machine translation systems are fast and easy to use for translating economic texts, they still need people to check for correct terminology and consistency in context. Consequently, the amalgamation of terminological databases, post-editing, and AI-driven adaptation methodologies is identified as the most efficacious solution.

**6. Outcomes and Discourse.** The findings of this study indicate that the challenges faced in the machine translation of economic terminology are multifaceted and intricate. Lexical-semantic, morphological-syntactic, pragmatic-cultural, and

technological issues are interconnected and substantially influence the overall efficacy of machine translation systems. Polysemy, synonymy, and context dependency are the primary factors contributing to the erroneous translation of economic terminology, indicating that these challenges remain inadequately addressed in both NMT- and LLM-based systems (Koehn, 2020; Baker, 2018).The primary findings demonstrate that contemporary machine translation systems, particularly those utilizing neural architectures, have attained significant success regarding grammatical precision and fluency. However, maintaining consistent terminology and achieving domain-specific accuracy—especially in economic texts—continues to pose challenges. The analysis indicates that the predominant errors stem from terminological inconsistency and contextual misinterpretation, attributable to the absence of parallel corpora and the restricted access to specialized terminological resources (Bowker & Pearson, 2002; Castilho et al., 2017). From a theoretical standpoint, this study enhances the comprehension of the correlation between economic terminology and machine translation. It emphasizes the significance of concepts such as terminological equivalence, standardization, and contextual translation in MT systems. Moreover, the results validate the significance of amalgamating terminological databases, post-editing, and AI-driven adaptive systems. These methods are very useful in real life for making translations better and making sure that economic communication is correct (Bowker, 2015; Koehn, 2020). From a practical perspective, the study illustrates the efficacy of the human-in-the-loop model in the translation of economic texts. Researchers found that using post-editing and terminology management systems cut down on mistakes by a lot. This validates that a hybrid translation methodology is the most effective strategy for handling real-world economic texts (O'Brien, 2012; Somers, 2003). The study also has a number of problems. First, the corpus used for the analysis is not very big, which could make it hard to apply the results to other situations. Second, the comparative analysis only looks at a few machine translation systems (Google Translate, DeepL, and ChatGPT), so it doesn't show how well other modern systems, like domain-specific MT models, work. Third, not every area of economic terminology is fully covered (Koehn, 2020), such as fintech or cryptocurrency terminology.

In conclusion, while machine translation has advanced considerably in handling economic terminology, accuracy in terminology and contextual relevance continue to pose significant challenges. Future research should concentrate on the development of extensive domain-specific corpora, the expansion of terminological databases, and the enhancement of AI-driven adaptive systems to tackle these challenges.

**7. Conclusion and Prospects.** This study has conducted a thorough examination of the principal challenges faced in the machine translation of economic terminology, emphasizing their lexical-semantic, morphological-syntactic, pragmatic-cultural, and technological dimensions. The results show that modern machine translation systems, especially neural machine translation (NMT) and large language models (LLMs), can make good translations of general texts. However, they still have problems with terminology inconsistencies, contextual errors, and standardization issues in

specialized fields like economic terminology (Koehn, 2020; Baker, 2018). The study's findings indicate that several critical factors are necessary to guarantee the precise translation of economic terminology. First, we need to make domain-specific term databases and glossaries bigger. Second, combining machine translation systems with post-editing and human supervision (human-in-the-loop) greatly improves the quality of translations. Third, adjusting NMT and LLM models to work better with economic texts can make them more accurate when it comes to terms. These methods can work together to make sure that economic translations are consistent and accurate (Bowker, 2015; O'Brien, 2012).

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