

ACCURACY ANALYSIS OF LEXICAL RESOURCES FOUND IN ECONOMIC NEWS ARTICLES TRANSLATED USING DEEPL

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ABSTRACT

This study aimed to explore how accurately DeepL translates lexical resources on specific topics written in news articles. This research employs Mona Baker's equivalence theory to analyze and identify the equivalence of translation produced by DeepL. The data were taken from 7 randomly selected news articles with the economy or business genre published under a digital news platform in Indonesia established in 2016 and was located in Central Jakarta. The selection of these articles was intended to reflect authentic language use that was recently used in economic reporting. The lexical resources for this study were specific terms used in economic domains identified using Cambridge Dictionary's "Business English" section as well as an Indonesian Glosarium Ekonomi. Based on the result of the analysis, the findings showcased a 100% accuracy for 70 lexical resources, indicating that DeepL is a reliable neural machine translation in handling economic terminology. The high accuracy that DeepL produced was linked to the nature of economic terms, where economic vocabulary was globally recognized and was also consistently used across languages, hence allowing universally used terms across nations. The second reason linked to its high accuracy was due to how advanced DeepL's advanced neural networks are. DeepL employs a Transformer architecture and attention mechanism, therefore allowing DeepL to be able to analyse sequences of texts by capturing contextual information efficiently. Additionally, with its system, DeepL was able to analyze more accurately in comparison to past models like Recurrent Neural Network, where it was showcased that past models struggled in translating a text, leading to loss of context and information. The final reason linked to its high accuracy is due to the large numbers of datasets. The growing number of users allows the developer to stay up-to-date and strengthen the model's ability in translating different languages. It further allows the developer to identify opportunities for improvement and innovation.

Keywords: DeepL, translation accuracy, Mona Baker equivalence, economic terms, news articles

ABSTRAK

Penelitian ini bertujuan untuk mengeksplorasi seberapa akurat DeepL menerjemahkan sumber daya leksikal pada topik-topik tertentu yang ditulis dalam artikel berita. Penelitian ini menggunakan teori ekuivalensi Mona Baker untuk menganalisis dan mengidentifikasi ekuivalensi terjemahan yang dihasilkan oleh DeepL. Data diambil dari 7 artikel berita yang dipilih secara acak dengan genre ekonomi atau bisnis yang diterbitkan pada platform berita digital di Indonesia yang didirikan pada tahun 2016 dan berlokasi di Jakarta Pusat. Pemilihan artikel-artikel ini dimaksudkan untuk mencerminkan penggunaan bahasa otentik yang baru-baru ini digunakan dalam pemberitaan ekonomi. Sumber daya leksikal untuk penelitian ini adalah istilah-istilah khusus yang digunakan dalam ranah ekonomi yang diidentifikasi menggunakan bagian Business English dari Kamus Cambridge serta Glosarium Ekonomi Indonesia. Berdasarkan hasil analisis, temuan menunjukkan akurasi 100% untuk 70 sumber daya leksikal, yang menunjukkan bahwa DeepL adalah mesin penerjemah saraf yang andal dalam menangani terminologi ekonomi. Akurasi tinggi yang dihasilkan DeepL dikaitkan dengan sifat istilah ekonomi, di mana kosakata ekonomi diakui secara global dan juga digunakan secara konsisten di berbagai bahasa, sehingga memungkinkan istilah-istilah tersebut digunakan secara universal di berbagai negara. Alasan kedua yang terkait dengan akurasi tingginya adalah kecanggihan jaringan saraf DeepL. DeepL menggunakan arsitektur Transformer dan mekanisme atensi, sehingga memungkinkan DeepL untuk menganalisis urutan teks dengan menangkap informasi kontekstual secara efisien. Selain itu, dengan sistemnya, DeepL mampu menganalisis secara lebih akurat dibandingkan dengan model terdahulu seperti Recurrent Neural Network, di mana ditunjukkan bahwa model terdahulu kesulitan dalam menerjemahkan teks, yang menyebabkan hilangnya konteks dan informasi. Alasan terakhir yang dikaitkan dengan akurasi tingginya adalah jumlah kumpulan data yang besar. Meningkatnya jumlah pengguna memungkinkan pengembang untuk tetap mengikuti perkembangan terbaru dan memperkuat kemampuan model dalam menerjemahkan berbagai bahasa.

Kata kunci: DeepL, akurasi penerjemahan, Mona Baker, terminologi ekonomi, artikel berita

INTRODUCTION

In the current fast-evolving news landscape, it is essential for journalists to convey information both swiftly and efficiently to their audiences. With the advent of Artificial Intelligence (AI), the translation of news has become markedly simpler and more efficient. Free online platforms such as DeepL Translation, Google Translate, and Microsoft Translator, along with advanced websites like ChatGPT, Gemini, and Perplexity, have become essential tools for journalists to translate news content rapidly. The benefits of utilizing these platforms include improved accessibility, reduced time expenditure, immediate communication, augmented human-machine collaboration, assistance with language barriers, and further development of linguistic research and education (Shahmerdanova, 2025). Consequently, journalists can navigate the rapid news landscape without the necessity of translating news texts verbatim.

Despite the rapid growth and ease, imperfections in using AI for translation still emerges. When using AI, the commonly found mistakes found are loss of semantic meaning, decontextualization, inaccurate cultural context and grammar and syntax mistakes (Doshi, 2024). Moreover, AI often struggles to translate idioms, subtle cultural references, and specialized terms, which are important for keeping the accuracy and meaning of formal texts found in news articles (Syafiee & Yaqin, 2025). The context-dependent meaning, limited domain-specific data has made AI unable to grasp certain resources, hence highlighting the need for human interpretation (Graziani et al., 2022).

If these translation errors were to persistently occur, it will distort not only the meaning, but also the delivery of the translation, hence leading to a miscommunication to the readers. Within the news publishing field, especially for the economic domain, news article plays an essential role as it does not only involve information sharing, but also as a support in economic forecasting by judging the audience's sentiment extraction. According to Barbaglia, Consoli & Manzan (2023), sentiment extraction refers to the process of assessing the tone of news articles to analyze whether it expresses optimism or pessimism about the economy. Sentiments in news articles is a tool that is great in forecasting the economy, showcasing a higher accuracy as news published through various digital platforms plays a crucial role in shaping expectations as well as influencing consumption and investment decisions. If an error in translation were to occur within these news articles, not only will it disturb the economy forecast, but also how the audience will perceive economic growth.

This problem shows a study gap which lies in the inability of AI to maintain and intended use, particularly when dealing with technical terms and context-sensitive expressions commonly found in news articles. News articles frequently depend on subtle language and exact terminology tied to particular subjects, making faithful meaning transfer crucial for upholding journalistic credibility. This gap underscores the pressing need to assess how effectively AI preserves both meaning and intended use when translating lexical resources within specific news topics. Thus, this study aims to examine how well AI can translate lexical resources while maintaining key semantic aspects in news articles, thereby enhancing translation accuracy and reliability in multilingual journalism.

RESEARCH METHOD

The data collected in this study consisted of 70 lexical resources derived from 7 randomly selected feature articles on a digital news platform. The lexical resources were specific terms used in economic domains, found in the Source Text (ST) in Indonesian and in Target Text (TT), which is the translated version of the ST that is translated entirely to English using DeepL. The study was limited to 70 lexical terms due to time constraints and to keep the analysis manageable. This number was considered enough to represent commonly used economic terms while still allowing careful evaluation. The terms were all taken from *Glosarium Ekonomi* as well as the Cambridge "Business Dictionary" section in assuring that it is a term used in the economic field.

In collecting the lexical resources, the data collection procedure was divided into several stages. The first stage was to randomly select 7 economic articles that had been published on digital news platforms. Second, each of the selected news articles was transferred to the comparison table instrument that was specifically created to analyze the data. The Indonesian news article was then placed under the "ST (Indonesia)" column. To achieve the target text, the third stage involved translating the Indonesian news article into English by using DeepL. Following the second step and the comparison table, the output of the translation was placed under "TT (English Translation)". To collect the lexical resources, the comparison table was then analyzed. *Glosarium Ekonomi* was employed to find and collect economic terms for both languages. Some terms may also be classified as economic terms following Cambridge Dictionary's business English section.

The process of analyzing the data was separated into several stages. The first stage involved collecting each lexical resource where the Indonesian economic terms were placed under “ST (Indonesian)” and the English economic terms under “TT (English)” following the analytical table. Each of the terms serves as the foundation in analyzing the accuracy.

For the second stage, the lexical resources were reviewed by a dictionary meaning comparison. This involves comparing the meaning using Cambridge Dictionary for the TT and Kamus Besar Bahasa Indonesia (KBBI) for the ST. Both dictionaries' definition of each economic term was used to check if they share the same intended meaning or not.

The third stage was assessing the economic terms using Mona Baker's theory of equivalence at the word level. Following Mona Baker 11 types of word-level non-equivalence which explained situations or conditions in which a lexical resource in the TT was unable to maintain the full intended meaning of the ST. In this stage, each economic term for each language was examined by comparing its meaning based on dictionary definitions and glossary references. If the analysis were to reveal a distortion, reduction or a shift in meaning that aligned with those under Mona Baker's inequivalence, the translation was classified as inequivalent. On the contrary, terms that preserved the intended meaning as confirmed by the dictionary and glossary reference were categorized as equivalent. In addition, when a TL term matched the standardized equivalent provided in the *Glosarium Ekonomi*, it was considered equivalent, as the glossary functioned as an accuracy benchmark for economic terminology. The results of the accuracy analysis were then placed under the “Evaluation” column as referred to the analytical table.

In the fourth stage, the lexical resources were then classified into three categories: Accurate, Slightly Accurate Word, and Not Accurate, following Fahreza & Sari (2024) and Oktavianus & Xenia (2024) lexical classification.

In the final fifth stage, the collected words were accumulated to draw a conclusion as to how accurate DeepL is in translating lexical resources of economic news articles. This accumulation involved counting the total of the lexical resources under Fahreza & Sari (2024) and Oktavianus & Xenia (2024) lexical classification. The total of each classification was then summed in order to calculate overall accuracy percentage. This percentage reflected how DeepL accurately handled economic lexical resources and to shed light on the strength and limitations of using DeepL as translation assistant.

RESULT AND DISCUSSION

Table 1. Lexical Accuracy Classification Total

<i>Accuracy of Translation</i>	<i>Frequency</i>	<i>Percentage</i>
Accurate	70	100%
Slightly Accurate	0	0%
Not Accurate	0	0%

As shown in Table 1, DeepL appears to perform reliably when translating economic terminology, as it was able to reach 100% accuracy. Some translations were accurate through both dictionary definitions and some translations were accurate as they retained meaning in both dictionaries as well as accurate as stated in *Glosarium Ekonomi*.

Table 2 showcases the result of the identified lexical resources from the Indonesian news articles as well as translated news articles.

Table 2. Lexical Resources Found from Analyzed Articles

<i>No.</i>	<i>ST (Indonesia)</i>	<i>TT (English)</i>
1	bursa	exchange
2	kripto	crypto
3	aset	asset
4	sekuritas	securities
5	saham	stock
6	perusahaan	company
7	blockchain	blockchain
8	pasar	market
9	produk	product
10	ekuitas	equity
11	perdagangan saham	stock trading
12	perantara	brokerage
13	swasta	private
14	tingkat inflasi	inflation rate
15	indeks harga konsumen	consumer price index
16	harga	price
17	inflasi inti	core inflation
18	inflasi	inflation
19	biaya hidup	cost of living
20	pajak	tax
21	bisnis	business
22	domestik	domestic
23	suku bunga	<i>interest rate</i>
24	bank sentral	central bank
25	manajer	manager
26	investasi	investment
27	produk domestik bruto (PDB)	gross domestic product (GDP)
28	fiskal	fiscal
29	ekonomi makro	macroeconomics
30	pendapatan	revenue
31	penjualan	sales
32	kurs	exchange rates
33	harga emas	gold price
34	tarif	tariff
35	penetapan harga	pricing
36	sektor	sector

37	konsumen	consumer
38	belanja	spending
39	diperdagangkan	traded
40	krisis keuangan	financial crisis
41	mata uang	currency
42	investor	investors
43	perdagangan	trade
44	daya beli	purchase power
45	tabungan	saving
46	phk	layoff
47	manufaktur	manufacturing
48	kemitraan	partnership
49	impor	imported
50	resesi	recession
51	utang	debt
52	anggaran	budget
53	defisit	deficit
54	keuangan	financial
55	pengelola	manager
56	transaksi	transaction
57	karyawan	employee
58	pertumbuhan ekonomi	economic growth
59	kerugian	losses
60	laba bersih	net profit
61	kontrak	contract
62	efisiensi	efficiency
63	divisi	division
64	laba	profit
65	perseroan	company
66	kinerja	performance
67	anak usaha	subsidiaries
68	konsesi	concession
69	komoditas	commodity
70	infrastruktur	infrastructure

An example of meaning retention across both dictionaries could be seen with “*bursa*,” where according to *Glosarium Ekonomi*, the English translation would be “bourses,” instead of DeepL’s “exchange.” Despite the difference, the translation that DeepL produces still preserved the same core concept meaning in both source language and target language. According to Cambridge dictionary, “exchange” was defined as “a place or organization where shares, currencies and commodities are bought and sold,” which matches with KBBI definition of “*bursa*” which was “*tempat memperjualbelikan saham, obligasi, dan sebagainya.*” This is an example of where despite a difference in output,

equivalence was still achieved. Additionally, in Mona Baker's terms, this corresponds to one-to-one equivalence as the term is straightforward and fits the propositional meaning.

In example of meaning retention for both dictionary and *Glosarium Ekonomi* could be seen with "aset," where the direct translation was "asset" as referred in *Glosarium Ekonomi*. The output aligned directly with DeepL where it indicates that the term was transferred into the target language without any modification. In their respective language, the meaning further showed an equivalence. According to Cambridge Dictionary, "asset" is defined as "something that is owned by a person, company, or organization, such as money, property, or land," which matches with KBBI definition of "aset" which was "*sesuatu yang mempunyai nilai tukar*," This showed an equivalence through both dictionary as well as *Glosarium Ekonomi* as well as another example of a propositional lexical meaning in Mona Baker's concept.

A unique case showcasing the ability of DeepL in maintaining the intended meaning could be seen with "blockchain." According to Cambridge Dictionary, the term is defined as "a system used to make a digital record of all the occasions a cryptocurrency (= a digital currency such as bitcoin) is bought or sold, and that is constantly growing as more blocks are added." As no term was equivalent in KBBI and *Glosarium Ekonomi*, this term would be an example of a loanword in a source text, which aligns with those stated by Mona Baker's example of inequivalence. However, in this case the term is still considered accurate. "Blockchain" is a culture specific item that could also be considered a modern concept. DeepL borrowed the term "blockchain" as it was a technical term. Following Mona Baker, "blockchain" in this case is a propositional lexical meaning and was not used as an expressive or evoked meaning. Therefore, despite it being a loan word at the source text, the translation is still accurate as the emphasis was that the term is used as a technical term, hence propositional meaning and not an expressive and evoked meaning.

The first factor contributing to the high accuracy level could be attributed to the nature of the terminology in the economic domain. The economic terminologies are formed by basic ideas that are shared across the field Economic vocabulary is globally recognized and consistently used across languages due to international trade, finance, and economic policy frameworks, which promote uniformity in term usage and minimize contextual ambiguity (Abrarovna, Sailike & Artuchi, 2021). The consistency of terminology is further reinforced by nationally and internationally recognized institutions, such as the Office for National Statistics and the International Monetary Fund, that enable and regulate economic reporting and data by establishing an economic glossary.

In addition to showcase the frequent term used in discourse of economy, the findings of this study showcased examples of various economic terms that were commonly used when discussing economics, such as "Inflation," "Tariff," and "Investors," which were terms recognized worldwide across languages, allowing minimal distortion in meaning. From the findings under an article, the term inflasi or "inflation" was repeated under the same news article over 13 times consistently and had no distortion in meaning, as the term was recognized globally, leading to little ambiguity. Under the Corpus of Contemporary English, the term "inflation" occurred 22,242 times under 8,108 texts, showcasing how deeply embedded economic terminology is within public discourse.

The second factor contributing to the high number of accuracies is likely linked to DeepL's advanced neural network system alongside its large datasets that are constantly updated following the feedback its users provide. This advancement has made it possible for the adoption of advanced neural machine translation models like the Transformer architecture, which DeepL leverages to process and translate more accurately than other previous models (Kamaluddin et al., 2024). The transformer architectures leverage self-attention mechanisms to extract contextual relationships throughout the whole sequence, thereby enabling a more refined interpretation of the input text (Naveen & Trojovskiy, 2024). In contrast, a previously used mechanism that DeepL uses like the Recurrent Neural Network (RNN) or Convolutional Neural Networks (CNNs), despite being reliable when it came to handling translation assignments, had a main disadvantage due to its pattern of processing. As a result, when contextual details are dispersed throughout a lengthy source text, NMT systems using Recurrent Neural Networks are inherently unable to deliver reliable translations (Cambedda, Nunzio & Nosilia, 2021). In comparison to earlier models like Recurrent Neural Networks, the Transformer, introduced by Vaswani et al. (2017), employs an attention mechanism that allows the model to process and consider the entire input sequence simultaneously.

DeepL's large number of datasets made it possible to build the mechanism. According to Kamaluddin et al. (2024), DeepL is able to recognize diverse contexts and produce translations that are more precise and appropriate due to its large dataset. . This large set of data presents the system with a

wide range of writing styles, idiomatic expressions, and domain-specific vocabulary. As a result, DeepL can produce translations that are more contextually appropriate and natural.

In creating a reliable and accurate translation, an example follows under the term "*model perantara*," which DeepL translates into "brokerage model" for its final output. The word "*perantara*" is defined in KBBI as "*orang yang menjadi penengah atau penghubung*," meaning an intermediary or connector person, which lacks a direct formal equivalent in economic discourse. However, in the final output, DeepL selects "brokerage," a term from the finance and economic genre according to the Cambridge Dictionary, defined as "an organization that buys and sells currency, shares, etc. for other people or organizations." This result showcases DeepL's strength in analyzing contextual relationships and domain-specific nuances rather than relying solely on sequential word-for-word passage translation.

The growing number of users and clients who have provided feedback on the platform drives all these continuous advancements aimed at keeping DeepL an up-to-date neural machine translator. According to Booth (2025), more than 200,000 clients use DeepL's services, a group that includes government institutions as well as over half of the Fortune 500 companies. By actively collecting and analyzing customer feedback, the organization is able to identify opportunities for improvement and innovation. This emphasis on user needs has led to continuous updates designed to refine features and strengthen the overall user experience (Kamaluddin et al., 2024)

CONCLUSION

To conclude, this study aimed to explore how accurately artificial intelligence translates lexical resources on specific topics written in news articles. The result of the study showed a 100% equivalence from 70 lexical resources, showcasing how DeepL was able to translate economic terminology and maintain its equivalence after translating from Indonesian to English. To achieve this number, factors that contribute were the nature of economic terminology and DeepL's advanced machine learning capabilities. The nature of economic terminology all relate the basic ideas of how products are created and consumed, how individuals and organizations cooperate in producing them, the tools and resources involved, the foundational system and the structures built upon it, and how demand and supply shape the market. With a standardized term, ambiguity is less likely to happen and distort the meaning of each term. Furthermore, DeepL created a more accurate translation with its advanced architecture. The large dataset that DeepL has enhanced the model's ability to accurately understand and translate different types of content. This broad collection exposes the system to varied writing styles, idiomatic expressions, and specialized vocabulary across domains. This accurate and notable difference in comparison to other translation tools is further supported by the wide range of users that constantly gives feedback that allows the developer to evaluate its capacity and identify future opportunities and innovation.

For future research, this study suggests employing other equivalence theories other than Mona Baker framework both for economic terms and other terms that are specific to their domains as it will open a diverse range of analytical possibilities that was not fully discussed. Future research may also expand their data sources. A variety of source text that is not limited to only news articles may increase the reliability as well as applicability since it will be able to capture a larger range of linguistics elements, variety of terms as well as usage of terms that are not limited to a certain context.

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