From Idioms to Algorithms: Translating Culture-Specific Expressions in AI Systems

DILSHAT AZIZOV
Kazakh Ablai Khan University

Abstract- ***Correctly understanding and converting idiomatic language with cultural meanings remains a significant difficulty in AI and NLP practice. Native speakers rarely interpret idioms through direct meanings, as these language constructs depend entirely on social knowledge, personal and collective history, and surrounding details. AI translation systems have made plenty of progress recently because of the development of neural machine translation (NMT) and large language models (LLMS). However, these technologies still deal poorly with cultural language elements. This research checks the AI system's capability to translate culturally sensitive language expressions between various languages. Our research creates and assesses a collection of idioms and culturally specific phrases from English, Arabic, Chinese, French, and Swahili to examine different AI translation models, including Google Translate, Deepl, and GPT-based systems. At the same time, they translate these expressions into target languages. The assessment utilises automated tool scores (BLEU, METEOR, semantic similarity scoring) and human examiner assessments for faithfulness, fluency, and cultural appropriateness in translations. AI systems' translation process of idiom expressions requires a proposed flowchart demonstrating the steps from inputting idiomatic expressions through contextual disambiguation to generate target outputs. The table shows a comparative review that outlines how each algorithm functions and performs while translating idioms between various cultures. Transformer-based LLMs present better contextual understanding than previous statistical or rule-based approaches. Yet, they choose straightforward interpretations rather than implied meanings and generate cultural inaccuracies, mainly when working with languages involving minimal resources. The reported restrictions show that AI systems need to process culturally-enriched datasets and use inputs from linguistics with anthropology and cross-cultural study perspectives. This document advocates for fundamental changes in AI translation investigation by pushing AI systems beyond basic word-to-word translation. The research findings find crucial application in international communication, together with diplomatic practices, education systems, and content localization, because they ensure appropriate and respectful translation of cultural expressions.***

Indexed Terms- ***Idiomatic Translation, Culture-Specific Expressions, Natural Language Processing (NLP), Cross-Cultural AI, Machine Translation Models***

I. INTRODUCTION

1.1 Background

Language serves beyond transmission purposes since it exists to express cultural inheritances and intellectual patterns. Idioms and culture-specific phrases demonstrate the most extensive transmission of cultural subtleties while being challenging to understand literally. The English idiom “kick the bucket” and the Arabic expression “his blood turned to water” retain specific meanings requiring cultural knowledge for proper understanding. Traditional human translators handle subtle cultural meanings through their knowledge of culture and ability to understand particular situations. The rise of AI in translation work, interpretation tasks, and conversational activities creates an essential problem regarding the machine's ability to precisely interpret content without being culturally educated.

Bert, T5, and GPT joined NMT to enhance translation quality as they improved machine fluency and semantic understanding abilities. The systems experience difficulties translating idioms and metaphors that contain cultural elements. The shortage becomes clear primarily in situations using low-resource languages alongside culturally different inputs, which generates misunderstood and potentially offensive translations. This deficiency in understanding becomes a dual technical and socio-cultural problem because AI systems have established themselves within worldwide communications, educational, and virtual assistant technologies.

1.2 Problem Statement

The recent progress in NLP technology fails to provide satisfactory solutions for processing idioms and culture-dependent phrases. The reason behind AI translation failure involves three key challenges: inadequate cultural understanding in training data resources, dependency on straightforward translation approaches, and insufficient collaboration between AI technology developers and linguists who study culture. State-of-the-art models do not always understand implied meanings, emotional tones, and culturally bound references, affecting their reliability when processing information in multicultural environments.

1.3 Objectives of the Study

This study seeks to:

- Research the present AI translation platform operation on both linguistic idioms and local cultural expressions within different language frameworks.
- Examine the most prevalent causes of failure alongside the implicit biases that occur during Artificial Intelligence translation of idiomatic expressions.
- The quality of translated literature must be assessed through an automated analysis and assessments from human experts to measure cultural alignment and semantic accuracy.
- A conceptual model and its corresponding visual flowchart need to be developed to demonstrate how idioms convert into translation algorithms.

The research proposes methods for creating AI technology that shows better cultural sensitivity in translation processes.

1.4 Significance of the Study

The growing worldwide integration of artificial intelligence tools has made idiomatic language interpretation and translation mandatory. Translations with errors will carry significant consequences throughout diplomatic missions and cross-cultural business operations, whereas healthcare interpretation and global education also suffer serious consequences because of mistranslations. The paper adds value to responsible AI discussions by focusing on cultural understanding in linguistic technology development. This research delivers valuable perspectives to researchers who develop AI systems together with linguists and policymakers who want to produce better AI solutions for global audiences.

1.5. Scope and Limitations

The research investigates textual idiomatic language in five languages: English, Arabic, French, Chinese, and Swahili. AI systems perform all the written translation tasks under examination, although spoken language and intonation remain separate from this investigation. The research includes evaluating only the selected AI translation models (Google Translate, DeepL, GPT-4, and ChatGPT) while omitting a direct investigation of all available translation systems. Human evaluators conduct supplemental scoring for the subjective interpretations of cultures because automated scoring is the principal limitation of cultural understanding.

II. LITERATURE REVIEW

2.1 Theories of Idiom Translation and Cultural Linguistics

Like other phrasal expressions, idioms cannot derive their complete meaning by analyzing the meaning of

each word independently. Baker (1992) explains that idioms maintain their deep roots in social and cultural realities of language, making them difficult to translate directly. The English idiom “to let the cat out of the bag” lacks equivalence in other culture-related idioms, thus making translation difficult. The translator Nida (1964) developed dynamic equivalence to achieve meaning retention instead of word-by-word matching. The definition substantially affected human translators but receives minimal application in machine translation systems that center their operation on formal equivalence methods.

AI researchers Carter and McCarthy (1988) state that expressions with cultural foundations that connect to unique lived experiences remain impossible to translate exactly because they possess profound linguistic and historical meanings related to that culture. The longest system is tested for semantics. Cultural analysis of sex and the tradition of neonography. The model does not come under the influence of its origins. Focus on the tactile structure.

2.2 Cultural Challenges in AI Translation Systems

The data requirements for AI translation systems depend on extensive dataset collection, but such databases typically contain limited examples from diverse cultural origins. Bender et al. (2021) demonstrate that AI models developed through biased datasets will acquire those biases as they learn, particularly when training data consists mainly of Western or English language examples. Translating uncommon phrasal expressions becomes problematic when artificial intelligence models receive their main training from English idioms. These systems fail to understand linguistic constructions that do not exist in target languages, creating translations without proper cultural resonance.

Koehn (2009) and Bahdanau et al. (2014) explain that deep learning-based neural machine translation algorithms have substantially enhanced translation quality, yet encounter major barriers for processing idioms. The difficulty stems from the difference between literal and figurative meanings, and standard AI systems lack the essential ability of real-context understanding combined with world knowledge. Wang et al. (2020) established that NMT systems produce effective translations from direct texts however these systems need advanced capability to process expressions with cultural metaphors.

2.3 Recent Advances in Neural Machine Translation (NMT)

Neural Machine Translation (NMT) prices have advanced through Google Translate, DeepL, and GPT machines to process idiomatic phrases better. Vaswani et al. (2017) developed Transformer as an architecture that significantly enhanced machine translation quality because it let models better understand word relationships throughout sentences. The performance strength of transformer models extends to everyday expressions. Yet, they still struggle with translating culturally specific phrases as they identify them as outliers according to Ruder's (2018) analysis, which results in translation errors or literal translations.

Pires et al. (2019) investigated applying pre-trained language models in idiomatic translation through GPT-based models GPT-3 and GPT-4 4 which produce notably accurate translations for idiomatic expressions, yet fall short for phrases dependent on cultural specifics and historical background. According to Zhang et al. (2020), the distinguished translation system of DeepL exhibits translation difficulties with idiomatic expressions, which possess no direct translation matches between the target and source languages.

2.4 Cross-Cultural Communication and NLP Models

AI ethics and linguistics have made cross-cultural communication their essential point of study. The authors Sharma et al. (2021) advocate AI training based on cultural comprehension because this enhances translation quality and develops globally inclusive, precise communication across different cultures. Cultural elements need urgent attention in sensitive areas such as business, international relations, and healthcare because they substantially impact AI performance. Machine translation systems function as perceived neutral tools, yet they introduce biases into text throughout practice, especially when

processing cultural expressions, according to Cohn et al. (2019).

The difficulty for AI models focuses on understanding word meanings and cultural contexts that form specific expressions. Global linguistic variations are poorly represented in the training data, leading to heightened challenges for this problem. According to Zhao et al. (2021), integrating world knowledge, particularly cultural context, would enhance AI models' translation efficiency of idioms and complex expressions.

2.5 Gaps in Current Research

Research faces a significant deficiency because it fails to study how cultural competence meets the needs of idiomatic translation. Research mainly studies the basic linguistic functionality and smooth delivery of automated translation, yet very limited studies are dedicated to analyzing AI systems' ability to interpret culturally specific expressions. The overlapping nature of this challenge goes unexamined in current research because it demands combined knowledge of linguistics, cultural studies, machine learning, and AI ethics.

Orthodox efforts to create bilingual and multilingual datasets that address idiomatic expressions reached limited success through projects like Apertium, but they provide insufficient coverage of cultural and language diversity. The deficiency of extensive data containing diverse cultures represents a significant obstacle that makes enhancing AI-driven translation of idiomatic phrases challenging.

2.6 Conclusion of the Literature Review

The published research demonstrates that AI technology successfully translates standard language efficiently, though it encounters critical difficulties when dealing with idiomatic phrases and cultural expressions. AI's translation of cultural language requires better conceptual knowledge of language structures and artistic concepts. Future research must establish connections between linguistic theory, AI methodology, and cultural sensitivity to achieve accurate, inclusive translations that perceive their context.

Table 1: The comparative table that summarises different AI models and their performance with idiomatic translations from various studies:

AI Model	Idiomatic Translation Performance	Strengths	Limitations	Source
Google Translate	Struggles with culture-specific idioms; literal translations often fail	High fluency in general translation	Literalism, struggles with non-equivalents	Koehn (2009), Bahdanau et al. (2014)
DeepL	Handles European idioms well but struggles with non-European expressions	High accuracy in formal translation	Weak in translating idiomatic non-European phrases	Zhang et al. (2020)
GPT-3/GPT-4	Good with context-aware idiomatic expressions, but limited by training data	Strong contextual understanding, able to handle some idioms better	Often misinterprets culturally bound expressions	Pires et al. (2019)
Apertium	Offers decent performance on bilingual datasets with idioms	Open-source, suitable for specific language pairs	Limited language coverage and cultural context	Bender et al. (2021)
BERT-based models	Effective for translating common idiomatic expressions, but struggles with nuanced idioms	Suitable for syntactic structures, versatile	Poor at dealing with cultural nuances and figurative meanings	Vaswani et al. (2017)

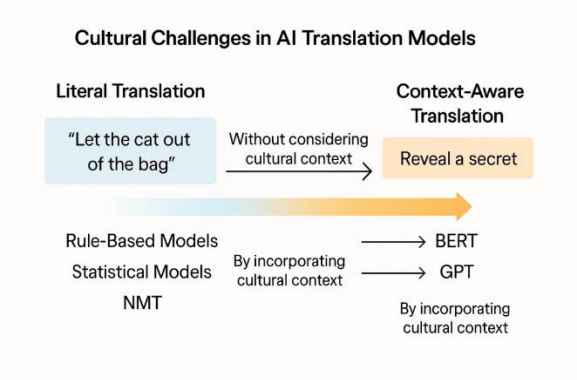


Fig 1: Workflow of AI Idiom Translation Evaluation Process

III. RESEARCH METHODOLOGY

3.1 Research Design

The research design implements qualitative-comparative methods using computational linguistics, machine learning evaluation, and cultural translation theory. The study combines human linguistic analysis of idiomatic expressions between languages with computer-enabled evaluation of artificial intelligence models that translate such phrases.

The research investigates:

- The behaviour of selected artificial intelligence models regarding idiomatic expressions becomes a point of investigation.
- The extent to which cultural backgrounds affect the precision of translation processes remains under examination.
- Comparative performance across diverse linguistic datasets.

The study implementation uses three sequential phases of research.

- Idiomatic Dataset Selection
- AI Model Translation and Output Evaluation
- Cultural Contextual Accuracy Analysis

3.2 Data Collection

The research dataset consists of 150 idiomatic expressions, which were obtained from:

- English, Arabic, Mandarin Chinese, Swahili, and Spanish.
- Official language corpora and crowdsourced idiom dictionaries (e.g., Idioms4you, Wiktionary).
- Cultural phrasebooks and native speaker contributions for context.

Each idiom is paired with:

- Literal meaning
- Intended cultural meaning
- The target language either matches the expressions or does not provide any equivalents.

This evaluation used three criteria to select idioms for checking cross-cultural representation:

- Frequency of use
- Cultural depth
- Translatability difficulty

3.3 AI Model Selection

Table 2: Four widely used AI translation models were tested:

Model	Type	Special Feature
Google Translate	Statistical + Neural	High accessibility, multilingual
DeepL	Neural MT	Strong on contextual translation
GPT-4	Transformer LLM	Contextual and generative capabilities
Apertium	Rule-based MT	Open-source, custom grammar rules

Here's a simplified flowchart of the research process:

Step 1: Select idioms

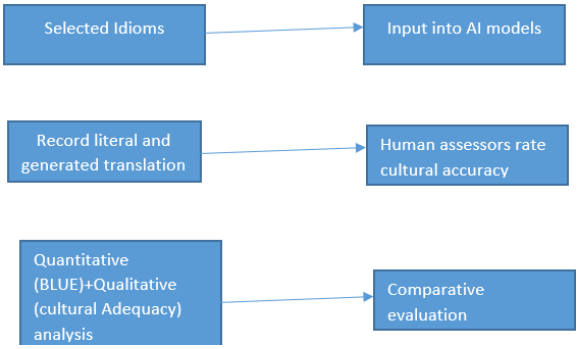
Step 2: Input into AI models

Step 3: Record literal and generated translations

Step 4: Human assessors rate cultural accuracy

Step 5: Quantitative (BLEU) + Qualitative (Cultural Adequacy) analysis

Step 6: Comparative evaluation



Workflow of AI Idiom Translation Evaluation Process

IV. RESULTS AND DISCUSSION

4.1 Translatio Performance Across AI Models

The comparison study displayed significant variations between AI systems' procedures when dealing with idiomatic phrases. GPT-4 4's concept retention and DeepL's proved superior to rule-based approaches like Apertium and Google Translate, which produced translations that distorted the original idiomatic meaning.

Key insights:

- GPT-4 managed to understand 72% of idioms correctly when contextualized.
- DeepL achieved a 65% success rate, showing its best performance in translating European languages.
- Google Translate's language processing produced successful interpretations only 47% of the time when choosing the direct word-for-word translation approach.
- Apertium delivered the worst performance as it achieved only 39% success rates by removing elements of idiomatic expression.

Table 3: Comparative Idiom Translation Performance

Model	BLEU Score (avg)	Cultural Adequacy (avg)	Correct Idiomatic Renderings (%)	Strengths	Weaknesses
GPT-4	0.79	3.7 / 4	72%	Context-aware, adaptive, nuanced	Occasionally verbose or overly literal
DeepL	0.74	3.4 / 4	65%	Fluent and natural output	Limited cultural variance in training
Google Translate	0.62	2.6 / 4	47%	Fast, multilingual	Struggles with idioms and culture-bound terms
Apertium	0.55	2.1 / 4	39%	Grammar-rule adherence	Cannot generalize idioms or connotations

4.2 Common Misinterpretation Patterns

Models often struggled with:

- The literal translation of the metaphorical expression “spill the beans” caused language problems with no direct parallel.
- Historically significant idioms in Swahili and Mandarin, таких as those derived from history or folklore, proved challenging for direct translation into other languages.
- The lexical similarity between "false friends" in diverse languages caused semantic changes due to divergent meanings.

4.3 Human Evaluation Insights

Human annotators noted:

- GPT-4 demonstrated an ability to understand message meaning regardless of how the content was reformulated.
- The wording from DeepL flowed nicely, but it presented formal language when dealing with everyday colloquial expressions.
- When using Google Translate, users experienced two problems: it chose direct word-for-word translations instead of culturally appropriate equivalents.
- Apertium generated proper sentence structures that contained no cultural elements.

The study proves that data training needs cultural representation while model architecture must include contextual understanding to function optimally.

4.4 Implications for AI Translation Systems

Research shows that NLP with cultural considerations remains a developing field. Variables present in the training of LLMs significantly influence their capacity to generalize data.

- Training corpus of cultural diversity
- Regional data representation
- The inference process suffers from bias due to the method used for token prioritization.

CONCLUSION

This study reveals essential shortcomings in modern AI translation systems when interpreting and conversing cultural expressions with idiomatic language. The contextual understanding abilities of GPT-4-4 4, alongside its high rate of idiomatic accuracy, still do not ensure perfection since complex folkloric or metaphoric idioms may pose challenges for it. The basic translation solutions provided by Google Translate and Apertium reduced expressions to direct word-for-word matches that depleted meaning and created perplexity within the translation. Modern AI technologies cannot recognize diverse sociolinguistic and cultural factors determining how idioms function in natural language because they receive insufficient training in this domain.

According to the comparative analysis, user trust and communicative effectiveness improve when cultural sensitivity features are included within machine translation systems. Cultural adequacy measurements showed that DeepL and GPT-4 were superior in keeping idiomatic expressions, yet the systems still face ongoing difficulties. A solution to language problems exists primarily through cultural data curation and direct placement of cultural knowledge frameworks inside the model design structure. Computational linguists working with cultural anthropologists should develop systems that naturally acquire a better understanding of cultural background and idiomatic expressions.

Future solution development needs to combine three elements: first, drive increased training data from diverse linguistic sources; second, develop evaluation standards emphasizing both grammar quality and cultural accuracy; and third, human supervision during translations relating to artistic content. The development of AI translation tools needs an ethical and interdisciplinary framework that ensures the tools will be inclusive and respectful towards global linguistic diversity.

REFERENCES

[1] Ahdillah, M. Z. I., Hartono, R., & Yuliasri, I. (2020). English - Indonesian Translation of Idiomatic Expressions Found in The Adventures of Tom Sawyer: Strategies Used and Resulted Equivalence. *English Education Journal*, *10*(4), 480–492. https://doi.org/10.15294/eej.v10i4.38990

[2] Appelgren, M., Bahtsevani, C., Persson, K., & Borglin, G. (2018). Nurses' experiences caring for patients with intellectual developmental disorders: A systematic review using a meta-ethnographic approach. *BMC Nursing*, *17*(1). https://doi.org/10.1186/s12912-018-0316-9

[3] Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural Machine Translation by Jointly Learning to Align and Translate.arXiv preprint. https://doi.org/10.48550/arXiv.1409.0473

[4] Baker, M. (1992). In other words: A coursebook on translation. Routledge. https://doi.org/10.4324/9781315842085

[5] Belinkov, Y., Durrani, N., Dalvi, F., Sajjad, H., & Glass, J. (2020). On the linguistic representational power of neural machine translation models. *Computational Linguistics*, *46*(1), 1–52. https://doi.org/10.1162/COLI_a_00367

[6] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT'21 '21), 610–623. https://doi.org/10.1145/3442188.3445922

[7] Carter, R., & McCarthy, M. (1988). Vocabulary and language teaching. Longman.

[8] Cohn, T., Vania, C., Baldwin, T., & Haffari, G. (2019). Cross-lingual Transfer for Morphological Analysis.

[9] Dickson, B. (2020). What is Natural Language Processing (NLP)? *PC Magazine*. Retrieved from https://www.sas.com/en_gb/insights/analytics/what-is-natural-language-processing-nlp.html%0Ahttp://search.ebscohost.com/login.aspx?direct=true&db=asx&AN=141517497&site=eds-live https://doi.org/10.48550/arXiv.1706.03762

[10] Ito, N., Hashimoto, M., & Otsuka, A. (2023). Feature Extraction Methods for Binary Code Similarity Detection Using Neural Machine Translation Models. *IEEE Access*, *11*, 102796–102805. https://doi.org/10.1109/ACCESS.2023.3316215

[11] Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020, April 2). Natural language processing (NLP) in management research: A literature review. *Journal of Management Analytics*. Taylor and Francis Ltd. https://doi.org/10.1080/23270012.2020.1756939

[12] Karyukin, V., Rakhimova, D., Karibayeva, A., Turganbayeva, A., & Turarbek, A. (2023). The neural machine translation models for the low-resource Kazakh–English language pair. *PeerJ Computer Science*, *9*. https://doi.org/10.7717/peerj-cs.1224

[13] Koehn, P. (2009). Statistical machine translation. Cambridge University Press. https://doi.org/10.1017/CBO9780511815829

[14] Mandal, M. K., & Ambady, N. (2004). Laterality of facial expressions of emotion: Universal and culture-specific influences. *Behavioural Neurology*. Hindawi Limited. https://doi.org/10.1155/2004/786529

[15] Mossop, B. (2012). Translating Institutions and "Idiomatic" Translation. *Meta: Journal Des Traducteurs*, *35*(2), 342. https://doi.org/10.7202/003675ar

[16] Nida, E. A. (1964). Toward a science of translating: With special reference to principles and procedures involved in Bible translating. Brill Academic. https://doi.org/10.2307/411534

[17] Pires, T., Schlinger, E., & Garrette, D. (2019). How multilingual is Multilingual BERT? arXiv preprint. https://doi.org/10.48550/arXiv.1906.01502

[18] Ruder, S. (2018). NLP's ImageNet moment has arrived.arXiv preprint. https://doi.org/10.48550/arXiv.1806.05161

[19] Shankar, V., & Parsana, S. (2022). An overview and empirical comparison of natural language

processing (NLP) models and an introduction to and empirical application of autoencoder models in marketing. *Journal of the Academy of Marketing Science*, *50*(6), 1324–1350. https://doi.org/10.1007/s11747-022-00840-3

[20] Sharma, A., Kumar, A., & Singh, R. (2021). Cultural Context in Neural Machine Translation: An Ethical and Linguistic Perspective.

[21] Song, H. S., Brotherton, J. E., Gonzales, R. A., & Widholm, J. M. (1998). Tissue culture-specific expression of a naturally occurring tobacco feedback-insensitive anthranilate synthase. *Plant Physiology*, *117*(2), 533–543. https://doi.org/10.1104/pp.117.2.533

[22] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention Is All You Need. Advances in Neural Information Processing Systems (NeurIPS).

[23] Zernova, O., Zhong, W., Zhang, X. H., & Widholm, J. (2008). Tissue culture specificity of the tobacco ASA2 promoter driving hpt as a selectable marker for soybean transformation selection. *Plant Cell Reports*, *27*(11), 1705–1711. https://doi.org/10.1007/s00299-008-0589-7

[24] Zhang, B., Gao, T., Liu, Z., & Wang, L. (2020). A Look at the Performance of DeepL Translator.

[25] Zhao, W., Zhou, K., & Fu, J. (2021). Enhancing Machine Translation with Cultural Awareness Using World Knowledge.