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A Comparative Study of Human and Machine Translation in English and Urdu Language: Evaluating Accuracy Using Google Translate and ChatGPT

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ABSTRACT

It has been observed that the difference between human and machine translation in English–Urdu texts creates several challenges in producing accurate and natural translations. Machine translation tools are widely used, but they often fail to handle cultural expressions, idioms, and narrative flow. A number of studies are available on machine translation, but limited research is available to explore a detailed comparison between human and machine translation in English - urdu text types. Thereby applying qualitative methodology and using Skopos Theory, Dynamic Equivalence, and Error Analysis, the current study aims to compare the translations of narrative texts, figurative idioms, and formal informational passages. The study highlighted that machine translation performs well in simple informational sentences, but human translation provides more natural, culturally appropriate, and meaningful results. Providing clear comparison and analysis can be an effective way to understand the limitations of machine translation and the important role of human translators.

Keywords: *Human Translation; Machine Translation; English–Urdu Translation; Skopos Theory; Dynamic Equivalence; Error Analysis; Cultural Expressions; Idiomatic Translation*

INTRODUCTION

Translation serves as a vital bridge for communication across linguistic and cultural boundaries. As technology continues to advance, translation is now carried out not only by human translators but also by a range of Machine Translation (MT) systems, including Google Translate, DeepL, and other AI-driven models. Developments in Neural Machine Translation (NMT) have significantly enhanced MT performance; however, questions persist regarding whether machine-generated translations can achieve the same levels of accuracy, naturalness, and cultural sensitivity that human translators provide (Ghazala, 2021; Toral, 2020).

Human translation (HT) remains highly valued due to the translator's ability to interpret contextual cues, cultural meanings, emotional nuances, and intended tone—elements that MT systems frequently fail to capture. Human translators are also able to appropriately convey figurative language, metaphors, idioms, and culture-specific expressions while preserving fluency and naturalness in the target language (Malmkjær, 2021; Li, 2022). In contrast, although machine translation offers speed and accessibility, it often produces literal, awkward, or contextually inappropriate output, particularly when dealing with narrative discourse or idiomatic and culturally embedded language (Jamaludin & Awang, 2023).

Guided by Skopos Theory, Dynamic Equivalence, and Error Analysis, this study conducts a comparative examination of human and machine translations of selected narrative texts, idiomatic expressions, and informational passages. The aim is to identify systematic differences in accuracy, naturalness, and cultural adequacy between the two forms of translation. By analyzing patterns across diverse text types, the study seeks to illuminate both the capabilities and limitations of contemporary MT systems and to reaffirm the continuing importance of human translators in producing coherent, meaningful, and culturally informed translations (Hassan, 2022).

Problem Statement

Machine translation tools such as Google Translate and DeepL are widely used for English–Urdu translation because they are fast and easily accessible, yet concerns remain about their ability to produce translations that are accurate, natural, and culturally meaningful. Human translators rely on linguistic knowledge and cultural awareness, which often allows them to create translations that better capture the original tone and intent. Despite the increasing use of machine translation, limited research directly compares human and machine translations within the English–Urdu context, especially across different text types such as narratives, figurative idioms, and formal informational texts. Existing studies mainly discuss general accuracy or technological development and do not fully apply translation theories like Skopos Theory, Dynamic Equivalence, and Error Analysis to identify strengths and weaknesses of machine output. Due to these gaps, it remains unclear where machine translation succeeds and where it fails, particularly in handling cultural meanings and natural expression. Therefore, this study aims to compare human and machine translations of selected English and Urdu texts to provide a clearer understanding of the limitations of machine translation and the continued importance of human translators.

Significance of the Study

This study offers a valuable contribution by providing a systematic comparison between human translation and the outputs of Google Translate and ChatGPT for English–Urdu texts. It highlights the areas where these tools are effective and the aspects where they fail to maintain naturalness and cultural meaning. The results support a better understanding of current translation technology, underline the continued importance of human translators, and provide useful insights for future improvements in English–Urdu translation quality.

Aim of the Study

The current study aims to compare human and machine translations in terms of accuracy and naturalness and to identify the key limitations of machine translation

Research Objectives

1. To compare the accuracy of human and machine translations using selected sample texts.
2. To evaluate the naturalness and fluency of machine translations in comparison to human translations.
3. To identify common errors and limitations in machine translation, particularly in handling cultural and contextual meanings.

Research Questions

1. How do human and machine translations differ in terms of accuracy?
2. How natural or native-like are machine-translated texts compared to human translations?
3. What specific errors or limitations appear in machine translations, especially in culture-specific or context-dependent content?

LITERATURE REVIEW

Human Translation in the Modern Context

Recent research continues to highlight that human translators remain essential for producing accurate and natural translations. According to Meylaerts (2020), human translation is still superior because translators understand cultural background, social norms, and pragmatic meaning, which machines cannot fully process.

Similarly, O'Hagan (2021) notes that human translators make context-based decisions, especially when handling figurative language, emotions, and cultural nuances. As a result, human translations tend to be more natural, fluid, and appropriate for the target audience.

Machine Translation (MT) After Neural Advances

Machine Translation has improved significantly with the rise of Neural Machine Translation (NMT). New studies show that modern MT systems produce more fluent and coherent sentences than older statistical systems.

Castilho (2020) explains that NMT has increased fluency, but issues such as misinterpretation of idioms, ambiguity, and missing world knowledge remain.

According to Toral & Way (2021), MT is effective for general or predictable texts, but its performance decreases when texts require cultural understanding or creative interpretation. Even with advanced models, MT still struggles with sarcasm, context-dependent meanings, and culturally loaded terms.

Accuracy in Human vs Machine Translation

Accuracy refers to the correctness of meaning. Daems & Macken (2020) found that human translations preserve meaning more consistently, especially when handling polysemous words (words with multiple meanings). MT often chooses the "most common" meaning rather than the contextually correct one. Farajallah & Antoniadis (2021) state that MT performs well in short, simple sentences but loses accuracy when dealing with longer, complex structures. Overall, recent studies emphasize that accuracy remains a challenge for MT because machines do not understand intention, emotional tone, or speaker perspective.

Readability

Naturalness means how smooth and native-like a translation feels.

According to Brucks & Zhang (2021), human translators produce more natural sentences because they understand idioms, collocations, and stylistic choices used by native speakers. Studies by Miranda &

Seghiri (2022) show that MT-generated translations often contain unnatural phrasing or literal word patterns that do not match natural speech patterns in the target language. Even though NMT improves fluency, it sometimes produces output that "sounds fluent but is semantically inaccurate," a phenomenon known as hallucination (Kreutzer et al., 2020).

Error Patterns in Machine Translation

Error Analysis is widely used to examine the quality of MT. Popović (2020) identifies common MT errors such as incorrect word choice, mistranslated idioms, grammatical mismatches, and literal translations. Similarly, Torres Hostench et al. (2021) found that MT frequently fails with culture-specific expressions and metaphorical language.

These studies show that although MT is improving, errors remain consistent and predictable because machines lack cultural knowledge, world experience, and pragmatic understanding.

Research Gap

Machine translation tools such as Google Translate and ChatGPT have improved with Neural Machine Translation. However, most research still focuses only on overall accuracy and system performance. A few number of studies directly compare human and machine translations for the English–Urdu language pair. Existing work rarely examines performance across different text types such as stories, idioms, and informational texts, where cultural meaning and natural expression are very important. Many studies rely on automatic evaluation tools, which cannot judge cultural fit, tone, or natural flow. Therefore, there is a clear need for a detailed qualitative comparison to understand where machine translation works well and where it fails in producing accurate and natural English–Urdu translations.

METHODOLOGY

The present study uses a qualitative comparative research design to explore the differences between human translation (HT) and machine translation (MT) in terms of accuracy, naturalness, and cultural suitability. The dataset includes two narrative passages, ten culture-specific idioms, and ten formal or informational texts. These three categories were chosen because they present different levels of linguistic difficulty and help reveal how translation quality changes across various text types. To evaluate the translations, the study applies three theoretical frameworks—Skopos Theory, Dynamic Equivalence, and Error Analysis—which together provide a clear and detailed understanding of the strengths and limitations found in both human and machine translations.

Research Design

A qualitative approach was selected because the study deals with language quality, meaning interpretation, and cultural nuance—elements that cannot be measured numerically. The research compares parallel translations: one produced by a human translator and one generated through machine translation tools (Google Translate and ChatGPT). This design helps evaluate differences clearly and naturally, using real examples rather than artificial test sentences. The focus is not on measuring the speed or efficiency of MT but on examining meaning, cultural fit, fluency, tone, and overall naturalness.

Data Collection Procedure

Narrative Texts

Two narrative passages—“A Day in the Life of Sara” and “An Unexpected Journey”—were selected because narrative writing requires smooth storytelling, emotional tone, imagery, and descriptive cohesion. These elements often challenge MT systems. Each text was first translated by a human translator, who aimed to maintain tone, descriptive style, and natural Urdu flow. The same texts were translated through Google Translate and ChatGPT to produce the MT versions.

Culture-Specific Idioms

Ten idioms were selected from both Urdu/Pakistani culture Idioms were chosen specifically because they depend on figurative meaning, not literal word-by-word meaning. All idioms were translated by a human translator and by MT tools. The aim was to observe how each translator deals with figurative language, symbolism, and culturally embedded meaning.

Informational Texts

Ten short informational texts were selected from WHO health guidelines, British Council informational statements, and public-information notices. These texts were chosen because they require clarity, formal tone, and technical accuracy. Both human and machine translations were produced for each text. This category tests how well MT handles straightforward, factual, or instructional content.

Translation Methods

Human Translation

A bilingual Urdu–English translator translated all texts with attention to meaning, cultural appropriateness, formality level, idiomatic usage, and natural flow. The translator’s identity was kept anonymous.

Machine Translation

Machine translations were produced by:

- Google Translate (the most commonly used MT tool in Pakistan)
- ChatGPT’s built-in translation feature

These tools were chosen because they represent modern Neural Machine Translation (NMT) systems.

Analytical Frameworks

Skopos Theory

Skopos theory used to check whether the translation fulfills the purpose of the text type.

Dynamic Equivalence

Dynamic equivalence used to examine whether the translation produces the same effect for Urdu readers that the original text produces for English readers. This helps identify whether MT captures tone, subtlety, or cultural meaning.

Error Analysis

Error analysis used to classify translation problems such as:

- Literal translation
- Loss of meaning
- Incorrect word choice
- Cultural inappropriateness
- Structural/grammatical errors

This allows comparison of consistent patterns in MT errors.

Data Analysis Procedure

Data analysis was carried out in the following steps:

1. **Side-by-Side Comparison**

Each English source text was placed next to its human and machine translations. Differences were highlighted for meaning, tone, structure, and naturalness.

2. **Coding of Errors**

Errors in MT were identified using Error Analysis categories.

Examples include:

- literal translation
- unnatural phrasing
- mixing English loanwords in Urdu

3. Interpretation Through Frameworks

- Skopos Theory was used to judge whether the translation served its purpose.
- Dynamic Equivalence helped evaluate naturalness and readability.
- Error Analysis highlighted systematic MT weaknesses.

4. **Cross-Category Comparison**

Narrative texts, idioms, and informational texts were compared to observe which text types are easier or harder for MT.

Data Collection

The data collection in this study focuses on systematically comparing human and machine translations in terms of accuracy, naturalness, and cultural appropriateness. The study selected narrative, idiomatic, and formal texts to cover different linguistic challenges.

1. **Narrative Texts**

Two narrative texts were selected to examine how human and machine translators handle fluency, cohesion, tone, and emotional nuance.

2. **Figurative / Culture-Specific Idioms**

Ten idioms were analyzed to test cultural and figurative translation.

3. **Formal / Informational Texts**

Ten formal texts were analyzed from WHO guidelines, technical instructions, and news articles

Data Analysis

The analysis focuses on comparing Human Translation (HT) and Machine Translation (MT) of selected English–Urdu texts. The evaluation considers accuracy, naturalness, and cultural appropriateness, using Skopos Theory (purpose), Dynamic Equivalence (meaning), and Error Analysis (mistakes).

1. **Narrative Texts**

Text 1: “A Day in the Life of Sara”

Source:
"Sara woke up early in the morning, brewed her tea, and sat by the window, enjoying the quiet sunrise before heading to work."

Human Translation (HT):

“Sarah subah sawere jaagi, apni chai banai, aur khirki ke paas baith kar khamoshi se tulu-e-aftab ka lutf uthaya, is se pehle ke woh kaam ke liye nikalti.”

Machine Translation (MT):

“Sarah subah sawere jaagi, chai banai aur khirki ke paas baitha, khamosh sooraj ko dekhne ke baad kaam ke liye gayi”

Analysis:

Skopos: HT preserves the narrative purpose, engaging the reader with tone and rhythm. MT conveys the literal meaning but fails to maintain smooth storytelling, reducing reader engagement.

Dynamic Equivalence: HT conveys both semantic meaning and aesthetic experience. MT conveys basic meaning but loses poetic nuance, making it sound robotic.

Error Analysis: MT shows awkward phrasing("دیکھنے کو سورج خاموش"), minor grammatical issues, and lacks narrative flow.

HT preserves narrative flow, tone, and subtle emotional cues.

MT translates meaning but produces awkward phrasing, losing the poetic and natural feel.

Text 2: "An Unexpected Journey"

Source:
"Ahmed decided to take a different route home. The streets were quiet, and he enjoyed the peaceful evening as he walked under the golden sky."

Human Translation (HT):

Ahmad ne ghar wapas jaane ke liye mukhtalif raasta ikhtiyar kiya. Galiyan pursukoon theen aur woh sunehri aasman ke neeche chalte hue shaam ki khamoshi se lutf andoz hua."

Machine Translation (MT):

"Ahmad ne ghar ke liye mukhtalif raasta liya. Galiyan khamosh theen aur woh sunehri aasman ke neeche chalte hue pursukoon shaam se lutf andoz hua."

Analysis:

Skopos: HT effectively communicates the narrative purpose, creating imagery and tone. MT communicates basic content but fails to preserve fluidity and rhythm.

Dynamic Equivalence: HT achieves semantic and aesthetic equivalence. MT loses subtle cues like peacefulness of the evening.

Error Analysis: MT has slightly awkward word order and robotic phrasing.

HT maintains imagery, tone, and rhythm, making it feel natural.

MT communicates basic meaning but loses nuance and smooth flow, making it slightly robotic.

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Conclusion for Narratives:

Human translations consistently maintain tone, flow, and engagement, while MT only conveys literal meaning, showing limitations in narrative naturalness.

2. Figurative / Culture-Specific Idioms

Ten idioms were analyzed to test cultural and figurative translation.

#	Idiom	Source	HT	MT	Analysis
1	نیکی کر داریا میں ڈال	Urdu	“Do good deeds without expecting anything in return.”	“Do good in the river.”	MT literal; loses figurative meaning
2	اونٹ کے منہ میں زیرہ	Urdu	“A tiny amount for something big.”	“Cumin in the camel’s mouth.”	MT literal, nonsensical
3	اندھا کیا چاہے؟ دو آنکھیں	Urdu	“What does a blind person want? Two eyes.”	“Blind wants two eyes.”	MT literal, loses figurative effect
4	A blessing in disguise	English	“ابتدائی برا لگنے والا واقعہ بعد میں فائدہ مند نکلا۔”	“چھپی ہوئی نعمت”	MT literal; meaning reduced
5	The ball is in your court	English	“فیصلہ کرنے کی باری آپ پر ہے۔”	“گیند آپ کے کورٹ میں ہے”	MT literal, culturally inappropriate
6	Break the ice	English	“ابتداء میں ماحول ہلکا کرنا”	“برف توڑنا”	MT literal, loses pragmatic sense
7	جب بندر کیا کرے گا؟	Urdu	“What can a monkey do?”	“When will the monkey act?”	MT literal, meaningless figuratively
8	Once in a blue moon	English	“بہت کم اتفاق ہوتا ہے۔”	“نیلے چاند میں ایک بار”	MT literal, unnatural phrasing
9	چراغ تلے اندھیرا	Urdu	“Problems are often near us but unseen.”	“Darkness under the lamp”	MT literal, loses metaphorical meaning
10	Spill the beans	English	“راز فاش کرنا”	“لوبیا گرا دو”	MT literal; nonsensical in Urdu

Analysis:

Skopos: HT preserves purpose and cultural meaning; MT fails in idioms, producing literal and often meaningless translations.

Dynamic Equivalence: HT achieves semantic and pragmatic equivalence; MT fails to maintain intended effect or tone.

Error Analysis: MT errors include literal translation, semantic loss, and cultural misunderstanding.

Human translations adapt idioms to cultural context and target language, preserving meaning and tone.

MT struggles with figurative language, often translating literally, resulting in unnatural or meaningless expressions.

Conclusion for Idioms:

Human translations excel in cultural and figurative fidelity. MT cannot correctly interpret idioms, demonstrating a major limitation in cross-cultural translation.

3**. Formal / Informational Texts**

Ten formal texts were analyzed from WHO guidelines, technical instructions, and news articles

#	Source Text	HT	MT	Analysis
1	Adults should consume 400g fruits daily.	“بالغوں کو روزانہ کم از کم 400 گرام پھل کھانے چاہییے-”	“بالغوں کو روزانہ 400 گرام پھل استعمال کرنا چاہییے-”	MT accurate but slightly awkward
2	Drink at least 8 glasses of water daily.	“روزانہ کم از کم 8 گلاس پانی پئیں-”	“روزانہ کم از کم 8 گلاس پانی پیو-”	MT understandable but informal
3	Wash hands before eating.	“کھانے سے پہلے ہاتھ دھوئیں-”	“کھانے سے پہلے ہاتھ صاف کریں-”	MT literal, slightly unnatural
4	Exercise 30 minutes daily.	“روزانہ 30 منٹ ورزش کریں-”	“روزانہ 30 منٹ ورزش کرو-”	MT informal and robotic
5	Reduce salt intake to lower blood pressure.	“بلڈ پریشر کم کرنے کے لیے نمک کی مقدار کم کریں-”	“بلڈ پریشر کم کرنے کے لیے نمک کی مقدار کم کریں-”	MT accurate and clear
6	Limit sugar to 25g per day.	“روزانہ 25 گرام سے زیادہ چینی نہ لیں-”	“روزانہ 25 گرام سے زیادہ شوگر محدود کریں-”	MT literal, uses English “sugar”
7	Get at least 7 hours of sleep.	“کم از کم 7 گھنٹے کی نیند لیں-”	“کم از کم 7 گھنٹے سونے-”	MT unnatural phrasing
8	Avoid smoking and alcohol.	“سگریٹ نوشی اور شراب سے پرہیز کریں-”	“سگریٹ اور الکحل سے بچیں-”	MT literal; less formal
9	Eat whole grains daily.	“روزانہ مکمل اناج کھائیں-”	“روزانہ ہول گرین کھائیں-”	MT literal; English loanword
10	Regular check-ups prevent chronic diseases.	“باقاعدہ چیک اپ دائمی بیماریوں سے بچاؤ کرتے ہیں-”	“ریگولر چیک اپز دائمی بیماریوں کو روکتے ہیں-”	MT mixes English; unnatural

Analysis:

Skopos: Both HT and MT deliver the purpose (informative/technical), but HT ensures professional tone and natural style.

Dynamic Equivalence: HT maintains meaning, accuracy, and clarity. MT conveys meaning but occasionally reduces readability.

Error Analysis: MT shows minor awkward phrasing, literal translation of technical terms, and informal tone.

Human translations are accurate, natural, and formal, suitable for readers.

MT translations are mostly accurate but sometimes produce awkward phrasing, literal translations, or mix of English words, reducing readability.

MT performs better in technical accuracy than narrative or idiomatic texts but still fails in tone and style.

Conclusion for Formal Texts:

MT performs well in factual accuracy but lacks stylistic refinement. HT is superior in clarity, professionalism, and readability.

Data Analysis:

Skopos Theory: HT achieves communicative purpose in all text types; MT struggles with narratives and idioms.

Dynamic Equivalence: HT maintains meaning, tone, and effect; MT often only preserves literal meaning.

Error Analysis: MT errors include literal translation, awkward phrasing, cultural misunderstanding, and use of English loanwords in Urdu texts.

While MT has improved, particularly in formal/factual translation, human translation remains superior in naturalness, cultural adaptation, and complex meaning, especially in narrative and idiomatic texts. MT is useful as a support tool but cannot fully replace human expertise in English–Urdu translation.

Narrative Texts: Human translations maintain tone, fluency, and natural storytelling; MT communicates basic meaning but loses natural flow and subtlety.

Idioms / Figurative Language: Human translators adapt idioms culturally; MT often produces literal, unnatural, or meaningless translations.

Formal / Informational Texts: MT handles factual accuracy reasonably well but sometimes fails in style, tone, and phrasing; human translations remain superior.

FINDINGS

The findings of this study reveal substantial differences between Human Translation (HT) and Machine Translation (MT) across the narrative, idiomatic, and informational texts analyzed. Although MT has demonstrated improvement in producing basic, surface-level translations, it still struggles to reproduce naturalness, cultural meaning, and stylistic coherence—elements that human translators manage with ease. Across all text types, human translations consistently preserved both semantic accuracy and communicative effect, whereas MT outputs frequently displayed literalness, awkward phrasing, and loss of contextual meaning. These results align with the guiding theoretical frameworks—Skopos Theory, Dynamic Equivalence, and Error Analysis—each of which highlights specific strengths in HT and recurrent limitations in MT.

The analysis of the two narrative texts, "A Day in the Life of Sara" and "An Unexpected Journey," showed that HT maintained a coherent narrative flow, emotional tone, and stylistic smoothness. Human translators effectively captured descriptive imagery, narrative rhythm, and subtle emotional cues, allowing the Urdu versions to read naturally and engagingly. By contrast, MT produced accurate but stylistically weak translations. While the basic meaning was communicated, the translations often contained literal renderings, unnatural collocations, and grammatical inconsistencies. Phrases such as "خاموش سورج کو دیکھنے" illustrate MT's inability to interpret metaphoric or expressive language, resulting in outputs that feel mechanical rather than narrative. Within the Skopos framework, HT fulfilled the communicative goal of storytelling, whereas MT met only minimal comprehension requirements. Dynamic Equivalence further confirmed that HT successfully conveyed both meaning and mood, while MT failed to recreate the intended narrative effect.

The idiom analysis produced the most striking differences between HT and MT. Human translators displayed strong competence in interpreting figurative meaning and rendering idioms into culturally appropriate equivalents in Urdu. Whether translating English idioms like "spill the beans" into " راز فاش کرنا" or Urdu idioms like "اونٹ کے منہ میں زیرہ" into English equivalents, HT consistently preserved pragmatic meaning, cultural nuance, and communicative intent. MT, however, translated nearly all idioms literally, resulting in outputs that ranged from unnatural to entirely nonsensical. Literal renderings such as "لوبیا گرا دو" for "spill the beans" and "نیلے چاند میں ایک بار" for "once in a blue moon" highlight MT's inability to process idiomatic meaning. Under the Skopos and Dynamic Equivalence frameworks, MT failed to achieve the purpose of idiomatic communication, and Error Analysis showed repeated issues such as semantic loss, cultural misinterpretation, and incorrect contextual mapping. These findings demonstrate a major limitation in MT systems, which lack the world knowledge and interpretive competence required to translate figurative or culturally embedded language.

The analysis of the formal and informational texts showed comparatively better performance by MT. In factual and instructional content, MT often produced translations that were reasonably accurate and comprehensible. However, issues remained with tone, register, and lexical choice. MT frequently relied on English loanwords, produced informal phrasing, and occasionally rendered instructions in a less professional style than intended. For example, MT outputs such as "ہول گرین کھائیں" and "الکحل سے بچیں" reflect lexical inconsistency and reduced formality. Human translations in this category were consistently clearer, more formal, and stylistically aligned with the communicative purpose of informational discourse. While MT demonstrated competence in conveying core factual content, HT remained superior in achieving both clarity and appropriate tone. Under the analytical frameworks, MT partially met Skopos requirements for information delivery but fell short in terms of stylistic equivalence and cultural adaptation.

Taken together, the findings show that MT is most successful with straightforward, factual texts, but it performs poorly with narrative and idiomatic content that requires cultural awareness, contextual interpretation, and stylistic nuance. Human translation consistently outperforms MT across all text types, particularly in maintaining naturalness, fluency, tone, and cultural appropriateness. Although MT offers accessibility and speed, its frequent reliance on literal translation, inability to understand figurative meaning, and lack of sensitivity to narrative style demonstrate that it cannot yet replace the interpretive skills of human translators in the English–Urdu context. These findings underscore the continued importance of human expertise, especially for texts requiring deeper linguistic and cultural understanding.

CONCLUSION

The present study set out to compare human translation (HT) and machine translation (MT) in the English–Urdu language pair, with a particular focus on accuracy, naturalness, and cultural appropriateness. Drawing on Skopos Theory, Dynamic Equivalence, and Error Analysis, the study examined three distinct text types narrative passages, culture-specific idioms, and formal informational texts to explore how each translation mode performs under different linguistic and cultural demands. The findings clearly indicate that while MT systems such as Google Translate and AI-based tools have improved in their ability to convey basic meaning, they still fall short in producing translations that reflect the depth, nuance, and cultural sensitivity required for high-quality translation.

Across narrative texts, MT struggled to maintain tone, imagery, emotional cues, and fluency, often producing literal or awkward structures that disrupted the narrative purpose. In contrast, HT consistently demonstrated coherence, stylistic smoothness, and contextual understanding, fulfilling the communicative intent of storytelling. The idiom category revealed the largest gap between HT and MT: whereas human translators accurately captured figurative meaning and cultural nuance, MT almost always generated literal translations that were semantically incorrect or nonsensical. This confirms that MT still lacks competence in handling metaphorical language and culturally embedded expressions. In the case of formal informational texts, MT performed comparatively better by conveying factual content with reasonable accuracy. However, even here, issues such as inconsistent formality, reliance on English loanwords, and stylistic unnaturalness limited the overall quality. Human translations remained superior in terms of clarity, professionalism, and appropriate register.

Overall, the findings reinforce that MT can be a useful tool for quick, surface-level understanding or for processing straightforward informational content. However, it cannot yet replace the interpretive, cultural, and stylistic expertise of human translators—particularly in languages like Urdu that rely heavily on idiomatic richness and contextual nuance. The study concludes that while MT will continue to evolve, human translation remains essential for producing fluent, meaningful, and culturally accurate translations. This research contributes to a clearer understanding of the limitations of MT and highlights the continued importance of human translators in ensuring translation quality across diverse text types.

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