Impact of Discourse Marker Accuracy on Translation Quality: Fluency, Coherence, and Patterns of Misuse in Machine Translation

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Abstract

This research explored the pivotal role of discourse marker (DM) accuracy in machine translation (MT) vs. human translation (HT) quality prediction in terms of fluency, coherence, and misuse patterns. The research, based on a mixed-methods design, quantified DM accuracy as precision, recall, and F1 scores, and qualitatively assesses text quality through human judgments and BERT-based coherence models. Findings showed that HT is much more accurate in DM (85–88% correlation with fluency/coherence) than MT (62–65%), with MT systems tending to overuse additive markers (and, so) and underuse contrastive/causal markers (but, therefore), and misuse however. These tendencies compromise discourse coherence, contribute to post-editing effort, and demonstrate the limits of BLEU-based measures in detecting discourse-level errors. The research calls for discourse-sensitive MT models, more informed evaluation metrics (e.g., Coh-Metrix, RST parsing), and pedagogical innovation in translator education to detect DM subtleties. Findings also pointed to ethical practice in MT-mediated communication and extend an invitation to cross-lingual research in low-resource language translation development. By combining theoretical linguistics and computational practice, the research takes steps forward in balancing DM-based errors and facilitating multilingual communication in a world that is progressively digitalized.

Keywords: Discourse markers, translation quality, fluency, coherence, machine translation, human translation

Introduction

Discourse markers (DMs) like however, therefore, and in addition play a crucial role in organizing textual discourse and indicating speaker intention, as highlighted by early research (Schiffrin, 1987; Jucker & Ziv, 2020). Not only do these markers ensure coherence, but they also convey pragmatic meaning, like contrast, causation, or elaboration, required to infer meaning beyond the literal (Fraser, 1999; Zufferey et al., 2021). Yet, their translation is particularly challenging owing to cross-linguistic formal and functional differences. For example, English but can be rendered as mais in French or pero in Spanish, yet these counterparts will have different connotations according to cultural and syntactic conventions (Hansen-Schirra et al., 2021). Such differences impose on translators the need to reconcile semantic, pragmatic, and contextual constraints—a demand that continues to challenge machine translation (MT) systems. MT systems, especially neural models (NMT), tend to mistranslate DMs because they are based on surface patterns and do not have good inference capability for discourse-level dependencies (Koehn & Knowles, 2017; Toral et al., 2020).

Although NMT has improved fluency at the local level, it lags behind in long-distance coherence, with high-frequency outputs that are grammatically well-formed but pragmatically discontinuous (Bawden et al., 2021). For instance, adversative DMs such as yet or nevertheless are typically incorrectly translated in German-English pairs, leading to sudden changes in argumentation (Tezcan et al., 2020). Likewise, zero-shot translation settings—where models have zero exposure to target-language discourse conventions—compound DM mistranslation, as seen for low-resource language pairs such as Swahili-English (Kumar et al., 2021). The impact of DM mistranslation extends beyond readability. Empirical evidence indicates that DM errors are responsible for 15–20% of post-editing effort, representing a significant extra cognitive load for human translators (Popović et al., 2021; Daems et al., 2019).

Eye-tracking studies also show that readers incur increased processing effort when reading misrendered DMs, which interferes with their discourse structure afterwards (Dahlström et al., 2023). These problems are further exacerbated by the inability of conventional evaluation metrics such as BLEU and METEOR to effectively penalize DM errors, obscuring their effects on perceived quality (Moorkens et al., 2022). These recent developments in computational discourse analysis, including graph-based coherence models (Li et al., 2020) and transformer-based alignment frameworks (Garg et al., 2022), offer promising avenues for tackling such challenges. However, their integration into MT pipelines is still under-explored, especially for low-resource or morphologically rich languages (Guzmán et al., 2021). This project takes these advances forward to examine how accuracy in DM influences translation quality, closing gaps among theoretical linguistics, computational modeling, and actual translation practices.

Literature Review

Theoretical Background

DMs are also significant with regards to textual coherence structuring and pragmatic interpretation. Though previous theories by Schiffrin (1987) and Fraser (1999) put DMs as linguistic devices for marking discourse relations, new paradigms have stretched their usefulness for multilingual and computational environments. For example, Jucker and Ziv (2017) redefined the functions of DMs in online communication, where they are used across genres with versatility. In computational linguistics, DMs are now embodied as crucial elements for discourse parsing in neural networks (Li et al., 2020), with studies indicating their role in

coherence enhancement in machine-generated text (Wang & Zhang, 2022). Zufferey et al. (2021) also examined cross-linguistic variation in DM usage, noting that languages like Mandarin and Arabic possess disparate DM systems from English, rendering translation more challenging.

Empirical Background

Empirical studies since 2015 have consistently identified DM mistranslation as a persistent weakness of machine translation (MT). Initial neural MT (NMT) models, despite advances, are beset by DM accuracy due to their reliance on local context windows, which fail to capture long-range discourse dependencies (Toral et al., 2020). For example, Castilho et al. (2017) demonstrated that statistical MT systems systematically mistranslated DMs like "however" and "therefore," resulting in incoherent output. More recent research by Tezcan et al. (2020) validated the findings, pointing out that even state-of-the-art NMT models (e.g., Transformer-based systems) fail to meet expectations when it comes to translating adversative DMs (e.g., "but," "yet") in German-English pairs. Similarly, Dahlström et al. (2023) used eye-tracking experiments to reveal that DM errors significantly disrupt human readers' processing fluency, substantiating the need for discourse-aware MT evaluation metrics. Gap in the Literature

While there is existing research that has addressed DM translation problems (e.g., Toral & Way, 2018), there remain gaps in knowledge about how specific DM errors affect downstream text quality. For instance, most research focuses on lexical or syntactic errors (Popović, 2023), without considering discourse-level flaws. Additionally, cross-lingual studies are scarce: there are hardly any investigations comparing DM misuse patterns in high-resource (e.g., Spanish-English) and low-resource (e.g., Swahili-English) MT systems (Guzmán et al., 2021). Also, as noted by Moorkens et al. (2022), current machine translation evaluation metrics such as BLEU and METEOR fail to punish discourse management errors sufficiently, causing a divergence between automatic and human coherence evaluations.

Problem

The accurate translation of DMs is indispensable for preserving text fluency and coherence, yet MT systems continue to exhibit systemic failures. For example, in NMT outputs, DMs like "actually" or "nonetheless" are often omitted or replaced with semantically incompatible alternatives, leading to abrupt shifts in discourse (Voita et al., 2019). Such errors are particularly pronounced in zero-shot translation scenarios, where models lack exposure to target-language discourse norms (Kumar et al., 2021). Compounding this issue, post-editing studies reveal that human translators spend 30–40% more time correcting DM-related errors than other error types (Daems et al., 2019), underscoring the economic and cognitive costs of poor DM handling. Despite these challenges, the precise relationship between DM accuracy and holistic translation quality remains underexplored, with most research focusing on isolated DM categories (e.g., contrastive vs. additive markers) rather than their cumulative impact (Bawden et al., 2020).

Objectives of the Study

This study aims to 1) Quantify the correlation between DM accuracy and translation quality metrics, using both human ratings and automated coherence scores (e.g., BERT-based discourse coherence models; Müller et al., 2020), 2) Identify patterns of DM misuse (overuse, underuse, mistranslation) in MT outputs across diverse language pairs (e.g., Chinese-English, Arabic-French), comparing them to human translation

benchmarks (Wang et al., 2020), and 3) Propose a taxonomy of DM translation errors to inform the development of discourse-aware MT systems, drawing on recent work in contrastive linguistics (Hansen-Schirra et al., 2022).

Novelty of the Study

This research is novel in the sense that it combines theoretical and applied perspectives to DM translation. Unlike earlier research on DMs as single words (e.g., Popović, 2023), this research has an integral framework whereby the impact of DM errors on discourse structure and reader engagement is considered. Methodologically, it combines recent developments in computational discourse analysis, including the use of graph-based coherence scores (Li et al., 2020) and transformer-based alignment models (Garg et al., 2022). In addition, by analyzing understudied language pairs and machine translation systems (e.g., multilingual BERT post-editing), the research responds to demands for greater linguistic diversity in machine translation research (Guzmán et al., 2021). Finally, its findings will play a part in the creation of continuous MT evaluation framework refinement, together with activities like the WMT 2023 shared task on discourse-level translation (Bojar et al., 2023).

Research Questions and Hypotheses

RQ1. To what extent do the discourse markers in human-translated and machine-translated texts correlate with the perceived fluency and coherence of these texts?

RQ2. What patterns of overuse, underuse, or misuse of discourse markers are characteristic of machine-translated texts compared to human-translated texts?

N_0. There is no significant correlation between DM accuracy and the perceived fluency and coherence of translated texts.

Significance of the Study

This study fills an urgent need in translation studies and computational linguistics in formally examining the discourse marker-translation quality connection. Theoretically, it contributes to translation theory by virtue of its integration of discourse-pragmatic theory and computational theories of coherence, fighting against reductionist tendencies of focusing on lexical and syntactic accuracy at the cost of discourse-level accuracy. By quantifying the degree to which DM errors disrupt discourse structure, the study offers empirical support for a more integrated approach to translation evaluation. It also contributes to cross-linguistic research by documenting variation in DM systems across language pairs, with significant implications for typological research. The findings enhance our understanding of how languages vary in managing discourse cohesion, with implications for both linguistic theory and translation practice.

Apart from theoretical insights, the study has significant practical and technological implications. Within machine translation, its findings can be utilized to inform the development of discourse-aware algorithms by incorporating state-of-the-art models such as graph-based coherence models or contrastive learning methods, which can particularly benefit low-resource languages. For translator training, the paper's taxonomy of DM errors is also a valuable pedagogical tool, allowing translators to identify and resolve

cross-linguistic mismatches, thereby reducing post-editing time and improving overall translation efficiency. Furthermore, improved DM handling in MT can help the performance of cross-lingual applications such as chatbots, legal translation, and multilingual content generation, where discourse coherence is paramount. The paper also raises ethical issues by highlighting how DM mistranslation can reinforce biases, leading to miscommunication in high-stakes areas such as medicine and diplomacy. In surmounting these challenges, this paper brings us nearer to the broad goal of developing more accurate, context-sensitive, and ethically sensitive translation technologies.

METHODOLOGY

Research Design

A mixed-methods approach is adopted to triangulate quantitative metrics (DM accuracy rates, coherence scores) with qualitative insights (human evaluations of fluency and coherence). This design aligns with recent calls for multidimensional translation quality assessment (TQA) frameworks that combine computational efficiency with human judgment (Dahlström et al., 2023; Müller et al., 2020).

Corpus of the Study

The study used two parallel corpora:

--Human Translation Corpus: 20 English source texts (news articles, academic abstracts, and technical manuals) and their professionally translated equivalents in French, Spanish, and Mandarin. These texts are selected for their diverse discourse structures and DM densities.

--MT Corpus: Translations of the same source texts generated by four commercial MT systems (Google Translate, DeepL, Baidu Translate, and Amazon Translate) and two open-source NMT models (MarianNMT, Opus-MT). Low-resource language pairs (e.g., Swahili-English) are included to assess cross-system variability (Kumar et al., 2021).

Instruments

The following instruments were used in the present study:

--DM Classification: Fraser's (2006) taxonomy is applied to categorize DMs into four functional classes: contrastive (however, but), elaborative (in addition, furthermore), inferential (therefore, thus), and topic-management (anyway, well).

--Coherence Metrics: BERT-based discourse coherence models (Müller et al., 2020) and Coh-Metrix (Graesser et al., 2020) are used to quantify textual flow.

--Human Evaluation: Native speakers rate translations on fluency (1–5 scale) and coherence (1–5 scale), following WMT 2023 guidelines (Bojar et al., 2023).

Data Collection Procedures

The data collection process for this study had a systematic framework to obtain diversity and reliability in the analysis of discourse marker (DM) translation. The source texts are chosen based on genre and DM density to ensure a representative mix of different linguistic and discourse structures. For generating translations, human translations were produced by expert professionals for providing high-quality reference texts, and machine translation (MT) outputs were obtained with default API settings for emulating real-world usage scenarios. Discourse markers in such texts were then identified using automatic extraction with spaCy's dependency parser. To determine the accuracy, human annotators checked the extracted data, with inter-annotator agreement greater than a Cohen's κ score of 0.85, indicating high reliability in the annotation.

Data Analysis Procedures

Qualitative and quantitative methods were employed in the study to analyze the data that has been collected. For quantitative testing, statistical testing such as ANOVA and regression compared DM performance across different MT systems and language pairs and provides empirical confirmation of error tendencies. Case studies also were applied to specific issues; namely, describing the way in which zero-shot translation—translating a model from one language to another without parallel training material—was responsible for increasing DM-related errors. The qualitative element enhanced these results through thematic coding of repeated error types, such as the mistranslation of actually as current in Spanish. To measure the broader discourse-level impact of these errors, the study employed Rhetorical Structure Theory (RST) to map coherence disruptions, offering a richer description of how mistranslated discourse markers affect textual cohesion as a whole.

RESULTS

Statistical Results of the First Research Question

Examining the Correlation Between DM Accuracy and Perceived Fluency and Coherence in HT and MT

One of the primary objectives of this study was to determine whether a significant relationship exists between DM accuracy and the perceived fluency and coherence of translated texts. To achieve this, Pearson correlation coefficients were calculated separately for HT and MT outputs. The results are presented in Table 1 below.

Table 1

Correlation Coefficients Between DM Accuracy and Perceived Fluency and Coherence

Translation Type	Fluency (r)	Coherence (r)
Human Translation (HT)	0.85**	0.88**
Machine Translation (MT)	0.62*	0.65*

Note: $p < 0.01$; $p < 0.05$

The correlation results indicate a strong positive relationship between DM accuracy and both perceived fluency and coherence in human-translated texts. Specifically, the correlation coefficients for HT were $r = 0.85$ for fluency and $r = 0.88$ for coherence, both of which are statistically significant at the 0.01 level. These results suggest that when DMs are used accurately in human translations, the resulting texts are perceived as significantly more fluent and coherent by evaluators. This aligns with previous research demonstrating that skilled human translators rely on DMs to enhance readability, ensure logical flow, and maintain coherence across sentences (Schiffrin, 1987; Taboada, 2018).

In contrast, while the relationship between DM accuracy and perceived quality in MT outputs is still positive, it is notably weaker. The correlation coefficients for MT were $r = 0.62$ for fluency and $r = 0.65$ for coherence, both of which are statistically significant at the 0.05 level. These results indicate that although DM accuracy plays a role in shaping fluency and coherence in machine-translated texts, other factors may contribute to lower overall quality. For instance, issues such as literal translations, misalignment with contextual meaning, and inconsistencies in DM usage may diminish the effectiveness of MT in producing naturally flowing discourse (Toral et al., 2020).

The results emphasize that while human translators integrate DMs effectively to construct coherent narratives, MT systems often struggle to maintain the same level of pragmatic appropriateness, leading to translations that may feel disjointed or mechanically structured. These results reinforce the need for improved discourse-aware models in MT development to bridge this gap.

Statistical Results of the Second Research Question

Analyzing Patterns of Overuse, Underuse, and Misuse of Discourse Markers in Machine Translation

A crucial aspect of this study was the systematic identification of DM-related errors in MT outputs. Specifically, the analysis aimed to detect recurring patterns of overuse, underuse, and misuse of discourse markers, which can contribute to translation errors and reduce text quality. A comparative assessment between expected and actual frequencies of selected DMs was conducted, and the results are displayed in Table 2 below.

Table 2

Frequency and Accuracy of Selected Discourse Markers in Machine Translation Outputs

Discourse Marker	Expected Frequency	Actual Frequency	Accuracy (%)	Error Type
And	150	220	68%	Overuse
So	80	130	62%	Overuse
But	90	60	85%	Underuse
Therefore	70	40	57%	Underuse

Discourse Marker	Expected Frequency	Actual Frequency	Accuracy (%)	Error Type
However	60	55	90%	Misuse

Interpretation of Results

The results reveal significant discrepancies between expected and actual DM usage in MT, highlighting systematic errors in how these markers are processed.

Overuse of "And" and "So"

Among the most prominent issues observed is the overuse of certain DMs, particularly "and" and "so." The actual frequency of "and" in MT outputs exceeded the expected frequency by 47%, while "so" was overused by 62%. This excessive reliance on additive markers suggests that MT systems may default to simpler, more generic connectors rather than selecting the most contextually appropriate transition words. Overuse of "and" can make the text feel redundant and excessively linear, while excessive use of "so" may lead to unnatural causality, where the logical relationships between ideas become forced or misleading.

Underuse of Contrastive and Causal Markers ("But" and "Therefore")

Conversely, certain discourse markers, such as "but" and "therefore," were significantly underutilized in MT outputs. The expected frequency of "but" was 90, whereas the actual frequency was only 60, indicating a 33% underuse. Similarly, the causal marker "therefore" appeared far less frequently than expected, with an underuse rate of 43%. These deficiencies may lead to texts that lack necessary contrast or logical progression, ultimately affecting coherence and readability. Without appropriate use of "but," opposing ideas may appear disconnected, while inadequate use of "therefore" weakens the explicit signaling of cause-and-effect relationships.

The results also highlight instances of misuse, particularly with the discourse marker "however." While this marker was used at a relatively appropriate frequency (55 instances compared to an expected 60), 10% of its occurrences were identified as incorrect or contextually inappropriate. Misuse of "however" often results in awkward sentence structures or unintended shifts in meaning, leading to confusion for the reader. This suggests that while MT systems may recognize the functional importance of certain DMs, they still struggle with nuanced contextual application, particularly in cases requiring contrastive transitions.

The above statistical analysis of DM usage in MT emphasizes several critical areas for improvement in current translation models:

--Reducing Overuse of Common DMs: MT systems must be refined to avoid excessive reliance on generic connectors like "and" and "so" and instead select DMs that align more precisely with semantic and pragmatic contexts.

--Enhancing Recognition of Contrastive and Causal Relations: Improving the accurate application of "but" and "therefore" will lead to better representation of logical discourse structures, ensuring that translated texts retain their intended argumentative flow.

--Context-Sensitive Application of DMs: Addressing misuse errors, particularly with markers like "however," will require enhanced discourse-aware modeling that integrates contextual information into translation processes.

These results provide valuable guidance for future enhancements in MT models, particularly in fine-tuning neural architectures to improve the coherence and fluency of machine-generated translations. Future research could explore the impact of advanced deep learning techniques, such as transformer-based discourse modeling, to address these persistent challenges in DM translation.

DISCUSSION

Discussion Related to the First Research Hypothesis

The results of this study strongly support the hypothesis that DM accuracy plays a crucial role in determining translation quality, particularly in relation to fluency and coherence. The correlation analysis revealed a significantly stronger relationship between DM accuracy and perceived fluency/coherence in human translation (HT) compared to machine translation (MT). These findings reinforce the notion that human translators, with their deeper understanding of context, pragmatics, and discourse structures, are better able to integrate DMs in ways that enhance textual cohesion (Taboada, 2018; Blakemore, 2020).

In contrast, MT systems, despite advancements in neural machine translation (NMT) architectures, continue to struggle with context-dependent use of DMs. The weaker correlations observed in MT suggest that while these systems can generate grammatically sound sentences, they often fail to accurately convey discourse-level relationships, leading to translations that may feel mechanical or incoherent to human readers (Toral et al., 2020; Sánchez-Gijón et al., 2023). This supports previous research indicating that traditional BLEU-based evaluation metrics may not fully capture discourse-level errors and that more discourse-aware assessment methods are needed (Scarton et al., 2023).

The findings suggest that improving DM handling in MT could lead to substantial gains in translation quality, making the text more natural and readable. Future improvements in MT model architectures should prioritize discourse modeling techniques that better account for DM selection and placement within the broader textual context (Way, 2021).

Discussion Related to the Second Research Hypothesis

The findings also confirm the hypothesis that MT systems often mismanage discourse markers, leading to distinct patterns of overuse, underuse, and misuse. Specifically, the results demonstrate a tendency for overuse of common additive DMs (e.g., "and" and "so"), while contrastive and causal markers (e.g., "but" and "therefore") are frequently underused. Additionally, misuse of DMs, such as incorrect placement of "however", contributes to disruptions in logical flow and semantic ambiguity.

These patterns indicate that while MT systems have improved in syntactic fluency, they still struggle with discourse-level pragmatics. This issue stems from the fact that current NMT models rely heavily on statistical co-occurrences of words rather than deeper contextual understanding (Koehn & Knowles, 2017). Unlike human translators, who can adjust DM usage based on situational and textual context, MT models often select DMs based on surface-level patterns rather than intended meaning (Bawden et al., 2021). Addressing this limitation will require enhanced context-aware architectures that incorporate: Discourse Representation Theories (e.g., SDRT; Asher & Lascarides, 2021), Transformer-based models trained on annotated discourse datasets, and Pragmatic and semantic role labeling to refine DM selection. These

improvements could significantly enhance the ability of MT systems to produce discourse-coherent translations, particularly for language pairs with substantial structural differences (Wang et al., 2022).

CONCLUSION

This study highlights the utmost significance of discourse marker (DM) accuracy in translation quality, particularly in fluency and coherence. The findings validate that human translators always produce more coherent and natural translations since they can use DMs in an accurate way in discourse structures. In contrast, MT systems are still beset with systemic errors in DM use in the forms of overuse, underuse, and misuse, which negatively impact readability and coherence.

The study's results carry important implications for MT algorithm development, such as the need for more sophisticated, discourse-oriented techniques of DM processing. Moreover, translator training courses need to cover extensive instruction in DM usage for improving translation quality across languages.

Implications of the Study

The findings of this study bear significant implications for pedagogic practice in the training of translators and for technical innovation in MT design. Because discourse markers (DMs) are the focal points that ensure textual coherence and fluency, there is an imperative to apply discourse-aware practices in translator training and in designing MT systems.

Theoretical Implications

Translation training programs must place greater emphasis on explicit teaching of discourse markers, particularly for students dealing with a number of pairs of languages that use different patterns of discourse markers. Since the selection of discourse markers is not necessarily one-to-one between languages, there is an urgent need for training curricula to prepare future translators with theoretical concepts as well as functional methods for handling the complexities effectively.

One of the key components of translator training needs to be the scientific study of discourse markers with a focus on their role in structuring discourse, establishing logical links between ideas, and securing textual coherence. Special attention must be given to language-specific DM variation, as the semantic, syntactic, and pragmatic functions of these markers are likely to vary across languages. Developing such an awareness will enable translators to make proper decisions that accommodate the discourse norms of the target language.

In addition to theoretical training, translator training should comprise experiential engagement with real machine translation errors of discourse markers. By studying human vs. machine translation differences, students are able to achieve deeper insights into frequent errors in the application of DMs. Practical exercises such as error tagging, comparative translation, and post-editing classes will better prepare them to identify and correct errors, ultimately enhancing their translation competence.

Strong theoretical foundations are also required for the understanding of discourse markers' nuances in translation. Training cognitive and linguistic models such as Segmented Discourse Representation Theory (SDRT) and Relevance Theory can provide students with effective analysis tools to make sense of the complex functions of DMs. These theories account for how discourse is structured and processed and how translators can build effective strategies for accurate DM choice, especially in translating between typologically far-from-each-other languages and possessing divergent discourse conventions.

Through the integration of these elements in translator training, future experts will be better able to produce fluent, well-structured, and pragmatically accurate translations and be cognizant of the limitations of current MT systems.

Practical Implications

The findings of this study are not only pedagogical applications but also make valuable recommendations to machine translation system developers, particularly regarding enhancing the way neural models handle discourse markers (DMs) in context. Despite the spectacular advances in neural machine translation, discourse-level coherence has been a hard nut to crack. Overcoming this limitation involves new modeling and evaluation approaches with discourse awareness in consideration.

A very crucial area of improvement is in developing machine translation models that well capture discourse-level dependencies. Current systems are primarily statistical co-occurrence based and local sentence-level context, and they disregard the general discourse functions of DMs. To achieve this, developers have to explore context-sensitive architectures with discourse-annotated training data and hierarchical transformers that can handle text at levels higher than single sentences. These advances would enable one to have a less overt understanding of DMs, ultimately resulting in meaning-preserving translations for extended discourse.

Another promising research direction involves tuning machine translation models with cognitive and empirical data. Eye-tracking experiments and post-editing tests provide strong evidence on how human translators process and employ DMs in real time. By integrating such cognitive signals, machine translation models could be adjusted to more realistically mimic human decision-making, raising the naturalness and contextual suitability of DM employment in translation.

In addition to the cognitive and structural enhancements, it is also necessary to reexamine how translation quality is measured. The classical metrics of BLEU, METEOR, and TER emphasize word-level accuracy and lexical similarity but tend to overlook the coherence and fluency of translated discourse. This study is important in its use of discourse-aware evaluation metrics, such as Coh-Metrix, GRADES, and HTER, that quantify logical coherence and text flow. Taking up these metrics, developers will be better equipped to comprehend machine translation performance and refine their models. Limitations of the Study While this study contributes meaningfully to the field of translation studies and to the field of machine translation studies, it is important to acknowledge its limitations. One limitation stems from the fact that it only addresses Arabic-English translation. While knowledge from this language pair is important, the particularity of its specific syntax and discourse patterns limits the generalizability of the findings to other languages. Other language pairs, such as Japanese-English or Chinese-French, may have unique challenges with DM translation that require investigation.

Moreover, the corpus employed in this research mainly contains formal text genres, such as news stories, legislation, and novels. Nonetheless, discourse markers behave differently in informal and spoken language, such as social media dialogues, conversational logs, and chat communication. Investigating machine translation systems' treatment of DMs in these forms may unveil substantial differences and possible shortcomings in existing models.

Another constraint lies in the assessment methods used. Although human evaluations and discourse-conscious metrics were considered, the integration of other computational methods, e.g., explainable AI models, would have given more profound insights into how and why MT systems commit particular errors regarding DMs. Understanding these limitations as a basis serves as a cornerstone for future work on improving and building upon this research.

Suggestions for Further Research

Based on the findings of this study, future research can explore other aspects of DM translation in machine translation, particularly in other languages, translation models, and thinking processes. Researching how machine translation systems translate DMs in typologically different languages could further reveal cross-linguistic challenges. Comparative analysis of different machine translation architectures—e.g., transformer-based architecture, GPT-based neural networks, and fine-tuned machine translation models—could further unveil the impact of discourse-aware adaptations on translation quality.

Experimental work training discourse-aware machine translation models on annotated discourse datasets would also provide valuable evidence of the effectiveness of discourse-aware learning. The application of human-in-the-loop approaches, in which translators provide real-time corrections to DM errors, could further enhance model fine-tuning and lead to more accurate translations.

Finally, adopting psycholinguistic approaches can offer a clearer view of how human translators translate DMs. Eye-tracking technology and cognitive load measurements can offer an insight into real-time decision-making, while working memory capacity studies can reveal the reasons why some DMs are overused, underused, or misused in machine translation. Pursuing these research tracks, the field can bring us closer to developing machine translation systems that produce discourse-aware, coherent, and contextually appropriate translations.

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