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Machine-Translated Language as a Distinctive Translational Variety: Evidence From a Multivariate Analysis of Discourse Connectives Across Text Varieties and Genres

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ABSTRACT

Machine-translated language is now produced and disseminated on an unprecedented scale, emerging as a new variety of translational language alongside human-translated language. Yet its linguistic characteristics remain insufficiently understood. Focusing on discourse connectives, this study integrated exploratory correspondence analysis with confirmatory linear mixed-effects modeling to examine the discourse-level features of machine-translated language. The results showed that: (1) machine-translated language differed significantly from human-produced language, including both human translations and human-authored original texts, in academic abstracts and/or government documents, with machine-translated texts favoring additive connectives and human-produced texts favoring causal connectives, suggesting a contrast between safer, more general connective choices in machine outputs and more semantically specific discourse marking in human productions; (2) machine-translated and human-translated languages, both as varieties of translational language, used more additive connectives in government documents than human-authored original texts, which showed higher frequencies of adversative and temporal connectives, reflecting shared features of translational language; (3) across most connective categories and genres, no significant differences were found between NMT and LLM-based MT, suggesting convergence and relative stability in connective preferences despite differences in underlying AI paradigms; and (4) genre significantly moderated connective use across text varieties.

摘要

本文聚焦语篇连接词, 系统考察神经机器翻译系统与大语言模型生成的机器翻译语言在语篇层面的特征。通过对应分析和回归建模, 研究发现:第一, 在学术摘要和/或政府公文中, 机器翻译语言更倾向于使用增列连接词, 人类产出语言则更倾向于使用因果连接词, 体现出两种语言独特的连接词使用特征。第二, 在政府公文中, 机器翻译语言与人类翻译语言均比人类原创文本更多使用增列连接词, 而人类原创文本则更多使用转折和时间连接词, 体现出翻译语言的独特性。第三, 神经机器翻译与大语言模型机器翻译在大多情况下均未表现出显著差异, 表明不同人工智能范式下的机器翻译语言在连接词使用上具有一定趋同性和相对稳定性。第四, 上述特征具有明显的体裁依赖性。

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1 | Introduction

Driven by the combined forces of big data, sophisticated algorithms, and increasing computing power, artificial intelligence (AI) has witnessed rapid advances in recent years. Machine translation (MT) is among the domains most visibly shaped by these advances, with MT systems achieving notable performance gains and becoming increasingly integrated into translation workflows. Against this backdrop, the agents involved in translation have expanded from human translators alone to include intelligent machine models, giving rise to a new translational ecology in which humans and machines coexist (Yu and Liu 2024). As a result, machine-translated language is now produced and disseminated on an unprecedented scale, emerging as a new variety of translational language alongside human-translated language.

The rapid proliferation of this emerging variety naturally raises the question of what linguistic features distinguish it from human-produced language. Since the advent of neural machine translation (NMT) (Sutskever et al. 2014) and, more recently, the rise of large language models (LLMs), research on the linguistic characteristics of machine-translated language has expanded substantially. While this growing body of work has produced important findings on lexical and syntactic patterning, discourse-level phenomena have received comparatively less systematic attention, despite a number of recent contributions in this area. Yet discourse is crucial to understanding machine-translated language, because it involves the encoding of semantic relations across clauses and sentences, as well as contextual interpretation and inference (Halliday and Hasan 1976), which have long posed challenges for MT systems. Among discourse-level features, connectives are particularly valuable for analysis because they overtly mark discourse relations and provide a relatively precise and measurable entry point into cohesion and coherence. A focused investigation of discourse connectives may therefore not only deepen our understanding of machine-translated language at the discourse level, but also help clarify persistent challenges in the handling of discourse relations in MT output.

Compared with research on machine-translated language, research on the linguistic features of human-translated language is far more mature. This line of inquiry can be traced back to the 1970s (Even-Zohar 2021) and expanded considerably in the 1990s with the establishment of corpus-based translation studies (Baker 1993; Ke 2005; Hu 2011). To date, it has continued to attract sustained academic attention. Existing research generally holds that the process of translation gives rise to recurrent linguistic regularities, often referred to as translation universals or general features of translation (Baker 1993), which were later reconceptualized as probabilistic tendencies (Chesterman 2004, 2016; Toury 2004, 2012). These patterns distinguish translated texts from both the source texts and target-language originals, thereby constituting translational language as a distinct linguistic variety.

Building on these well-established findings concerning the linguistic patterns of human translation, it becomes important to ask whether machine-translated language displays similar or different tendencies. Although machine-translated language has increasingly been examined in its own right, it has not yet been systematically integrated into the broader comparative framework of translational language, especially at the discourse level and across genres. The present study seeks to fill this gap through a cross-genre comparison of discourse connective use in texts produced by NMT systems, LLM-based MT systems, human translators, and human authors.

2 | Literature Review

2.1 | Studies on the Linguistic Features of Machine Translation

Existing studies on the linguistic features of machine-translated language can be broadly grouped into three strands. The first strand of research focuses on the universal features of machine-translated language or machine translations, including explicitation, simplification, normalization, source-language interference or shining through, and convergence, among others. Related studies compared machine translations with human translations or target-language originals using lexical and syntactic indicators such as type-token ratio, lexical density, word-class distribution, punctuation frequency, syntactic complexity, function-word use, and dependency grammar. While some studies confirmed tendencies toward normalization (Lapshinova-Koltunski 2015; Kuo 2019; Luo and Li 2022) and source-language shining through (Lapshinova-Koltunski 2015; Kuo 2019; Li and Hu 2024), findings on simplification (Han and Jiang 2016; Luo and Li 2022; Niu and Jiang 2024; Jiang 2025) and explicitation (Lapshinova-Koltunski 2015; Han and Jiang 2016; Krüger 2020; Kuo 2019; Bizzoni et al. 2020) remained mixed across datasets, genres, and methods.

The second strand is concerned with the model-specific or idiosyncratic features of MT output. These studies compared machine translations with human translations or original texts across lexical and syntactic features, including modal verbs, sentence-final particles, lexical diversity, word length, sentence length, syntactic simplicity, and dependency distance (Jiang 2014; Loock 2020; Frankenberg-Garcia 2022; Kolb et al. 2023; Liang and Liu 2023; Shen and Huang 2024). Their findings suggested that MT output tended to be more literal, exhibited lower lexical variety, and aligned more closely with source texts in information organization and textual construction, while also revealing difficulties in word-sense disambiguation, modal interpretation, and the explicit encoding of implied relations.

The third strand of research addresses the mechanisms underlying the linguistic features of machine translations. Much of this research linked MT regularities to the properties of data-driven systems (Vanmassenhove et al. 2019, Vanmassenhove et al. 2021), for instance, argued that probabilistic computation and pattern matching could introduce "algorithmic bias," amplifying high-frequency patterns present in the training data while reducing or even eliminating less frequent alternatives. Their comparison of machine-translated output with human translations in the training corpora provided empirical support for this account.

Although most earlier studies concentrated on lexical and syntactic features, a smaller body of research has recently begun to investigate discourse-level properties of machine-translated language. Using indicators such as complex network structures, theme-rheme progression, and verbal and referential links, studies by Niu et al. (2020), Jiang and Niu (2022a, 2022b), and Liang

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and Liu (2023) suggested that MT output exhibited tendencies toward explicitation and simplification at the discourse level, while still facing difficulties in producing coherent discourse organization. In addition, Konovalova and Toral (2022) found that human and machine translations differed in ways that affected the extraction of literary character networks, suggesting that translation mode influenced relational and discourse-level structure beyond the sentence level.

Another line of work also highlights the importance of genre or register in shaping translation features. Lapshinova-Koltunski (2015, 2017) demonstrated that both text register and translation method were important dimensions influencing variation in translated texts. More recently, Li and Gao (2025) showed that cohesive and coherent patterning in Chinese-English translation varied not only across human-translated, machine-translated, and non-translated texts, but also across registers, with register divergence exerting a substantial effect on translation features. Their findings suggested that translation variety could not be fully understood without taking genre or register into account.

With the emergence of the "pre-training + fine-tuning" paradigm, research on LLM-based translation has also begun to expand. For example, Yu (2024) reported that ChatGPT translations showed advantages in lexical richness and syntactic complexity, and Jiang (2025) found that LLM translation could also be investigated within the framework of translation universals. In more recent studies, Huang and Cheung (2026) found that AI models still differed from human translators in handling discourse-rich literary material, while Li and Gao (2025) showed that variation across translation types remained strongly conditioned by register. Together, these studies indicated that LLM-based MT should not simply be assumed to supersede NMT output in all respects, but rather needs to be examined empirically across genres and comparison baselines.

2.2 | Connectives in Translation Studies

Connectives have long been recognized as an important resource for textual cohesion and discourse organization. In the existing frameworks, connective or conjunction is not merely a local grammatical device, but a central means of signaling semantic relations across stretches of discourse (Halliday and Hasan, 1976; Zufferey and Degand 2024). This perspective has been particularly influential in translation studies, where shifts in connective use are often understood as part of broader shifts in cohesion and coherence in translation (Blum-Kulka 1986). From this viewpoint, connectives serve as a useful analytical resource for investigating how discourse relations are reorganized when texts are transferred across languages and reproduced under different conditions of textual production.

Within translation studies, connective use has often been discussed in relation to explicitation, that is, the tendency to make explicit in the target text information that is only implicit in the source text (Blum-Kulka 1986; Baker 1993). Halverson et al. (2004) identified connectives as a recurrent translation problem, since translators must decide whether discourse relations should be made more explicit or left implicit. Corpus-based studies showed that connective shifts were frequent in translation, but did not support a simple or universal account of explicitation. Becher (2011), Denturck (2012), and Zufferey and Cartoni (2014) all suggested that connective behavior was shaped by relation type, translation direction, and local context rather than by translation status alone. Puurtinen (2003) likewise showed that translation-specific differences could emerge in clause connectives, though not as a simple overall increase in connective use, while Song (2022) further demonstrated that connective explicitation could vary even across different translations of the same source text.

Research has also highlighted the sensitivity of connective use to genre and mediation mode. Zufferey and Degand (2024) showed that connective choice was shaped by genre, as different genres impose different rhetorical and discourse-organizational demands. Meyer and Webber (2013), in turn, reported that implicitation of discourse connectives was much less frequent in machine translation than in human translation, suggesting that machine systems were less likely to leave discourse relations implicit. In addition, Jiang and Niu (2022b) demonstrated that discourse-level features such as connectives provided an important perspective for distinguishing machine-translated language from other text varieties.

2.3 | Research Questions

Taken together, existing research provides an important foundation for understanding the linguistic features of machine-translated language, but important gaps remain. First, although some discourse-level features have begun to receive attention, discourse connectives warrant closer examination because they overtly encode discourse relations and thus offer a measurable basis for analyzing cohesion and coherence in text. However, research specifically focusing on connectives in systematic comparisons across machine translations, human translations, original texts, and genres remains limited. Second, although genre and register have increasingly been recognized as important variables in studies of translation features, their role has not yet been systematically examined in research specifically focusing on discourse connectives. Third, most previous work has focused on NMT, while the discourse-level characteristics of LLM-based translations remain comparatively under-investigated. Although NMT and LLM-based MT adopt different AI paradigms, both are grounded in neural network architectures, distributed token representations, and attention-based processing. Yet it remains unclear to what extent the linguistic patterns of these two paradigms differ, and whether machine-translated language exhibits sufficiently stable and systematic discourse features across them to be considered a distinctive translational variety.

In response to these gaps, the present study investigates discourse-level features of machine-translated language by focusing on discourse connectives as key markers of cohesion and coherence. It draws on a multi-genre comparable corpus comprising machine-translated texts produced by both NMT systems and LLM-based systems, alongside human-produced texts, namely human translations and human-authored original texts. By adopting a multivariate analytical framework, the study examines the distributional patterns of discourse connectives across text varieties and genres. The specific research questions are as follows:

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1. To what extent is machine-translated language, as an emerging variety of translational language, distinct from human-produced language, including human translations and human-authored original texts, in the use of discourse connectives?
2. To what extent are machine-translated and human-translated language, both as varieties of translational language, similar to each other in the use of discourse connectives when compared with original texts?
3. How do NMT and LLM-based MT, both as varieties of machine-translated language but adopting different AI paradigms, differ in their use of discourse connectives?
4. Does genre significantly influence discourse connective use across different text varieties?

3 | Methods

3.1 | Materials

To address the research questions outlined above, we constructed a balanced comparable corpus covering three genres: contemporary novels (CN), government documents (GD), and academic abstracts (AA). The corpus was composed of six text varieties, including two neural machine translations (Google and DeepL), two large language model-based machine translations (ChatGPT and Claude), human translations, and target-language original texts. All translations were produced in the Chinese–English direction. Corpus compilation followed three principles: comparability across text varieties in terms of publication/production time, subject matter, text length within each genre, and overall number; representativeness of source-text authors, target-language original authors, and translators; and balance across genres.

Chinese contemporary novels were collected from works by Chinese literary masters, including Yan Mo, Pingwa Jia, Hua Yu, Jia Mai, etc. The source texts for the government documents subcorpus were drawn from the *Report on the Work of the Government* (RWG), an annual report delivered by the Chinese Premier at the session of the National People's Congress of the People's Republic of China. Chinese academic abstracts were selected exclusively from the field of translation studies, on the grounds that translators of abstracts who are themselves translation studies researchers may consciously intervene in the translation process. It should be noted that academic abstracts here were treated as a distinct and highly conventionalized genre in their own right rather than as representative of academic writing as a whole, and this should be taken into account when interpreting the cross-genre findings.

Human translations were selected on the basis of the translators' professional standing and recognized expertise. For example, the contemporary novels were translated by prominent sinologists such as Howard Goldblatt, Michael Berry, and Michael Duke, while translations of government documents and academic abstracts were taken from officially released or published sources. For contemporary novels, English originals were selected from works by widely recognized contemporary authors in the English-speaking world. For government documents and academic abstracts, original English texts were selected from comparable institutional and disciplinary sources, respectively.

Machine translation systems were chosen for their broad recognition and representativeness. Google Translate and DeepL were included as NMT systems, and ChatGPT-5 and Claude 4 Sonnet represented LLM-based MT. All four systems have been widely used in translation practice and recent contrastive studies of translation varieties (e.g., Frankenberg-Garcia 2022; Kolb et al. 2023; Shen and Huang 2024; Yu 2024). Given that discourse connective use relies heavily on contextual and semantic inference, machine translations were generated at the document level to preserve contextual integrity. All machine translations were produced from scratch without pre- or post-editing. Detailed corpus information is provided in Table 1.

Previous research has shown that prompt design significantly influences LLM translation output. Key factors include the choice of translation unit (sentence vs. document) (Jiao et al. 2023; Wang et al. 2023), the explicit specification of translation direction, and the inclusion of genre information (Gao et al. 2023). In line with these findings, the present study explicitly specified the translation unit (document), translation direction (Chinese–English), and genre in the prompt design. Translation instructions can also vary in wording, such as "translate," "provide translation for," or "what's the meaning of/what do these sentences mean." Drawing on prior empirical evidence, the instruction "provide translation for" was adopted, as it has been shown to yield stable and high-quality translation performance (Jiao et al. 2023; Gao et al. 2023). The final prompt used in this study was as follows:

"This is a [SOURCE TEXT] to [TARGET TEXT] translation task. Please provide the [TARGET TEXT] translation for this document taken from the [SPECIFIC GENRE]."

3.2 | Connectives

According to Halliday and Hasan (1976), discourse connectives are defined as linguistic items that signal relations within discourse and play a crucial role in organizing texts and maintaining cohesion and coherence. Theoretically, a higher relative frequency of connectives tends to be associated, within a certain range, with greater discourse cohesion and coherence, with a positive correlation between the two (McNamara et al. 2014).

In terms of the classification of discourse connectives, the present study focused on four main categories, namely causal (Caus), adversative (ADC), temporal (Temp), and additive (Add) connectives, following the taxonomy proposed by Halliday and Hasan (1976). This classification laid the foundation for the categorization of discourse connectives in discourse analysis and subsequently served as an important theoretical basis for computational tools such as Coh-Metrix (McNamara et al. 2014). Detailed information on each type is provided in Table 2. To ensure comparability across texts of different lengths, the frequency of each connective type was normalized per 1000 words. The relative frequencies were automatically calculated using Coh-Metrix, a tool developed on the basis of a multi-level theoretical framework of discourse and language. Coh-Metrix was specifically designed to quantify various dimensions of

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TABLE 1 | Basic information on the corpus.

Genre	Text variety		No. of texts	No. of words	Publication/ production time
Contemporary novels (CN)	Human		52	89,336	2000–2015
	Machine	Google	52	82,537	Transl.2023.2
		DeepL	52	80,400	
		ChatGPT	52	66,632	Transl.2025.8
		Claude	52	81,416	
	Original		53	86,765	2004–2010
	Total		313	487,086	/
Government documents (GD)	Human		51	65,417	2010–2012, 2014–2015
	Machine	Google	51	58,622	Transl.2023.2
		DeepL	51	58,202	
		ChatGPT	51	55,182	Transl.2025.8
		Claude	51	58,038	
	Original		51	41,695	2010–2015
	Total		306	337,156	/
Academic abstracts (AA)	Human		52	7045	2000–2015
	Machine	Google	52	7817	Transl.2023.2
		DeepL	52	8229	
		ChatGPT	52	7500	Transl.2025.8
		Claude	52	7705	
	Original		52	7693	2000–2015
	Total		312	45,989	/

TABLE 2 | Operationalization of discourse connective measures.

Indicator	Operational definition	Examples
Relative frequency of causal connectives (Caus)	The ratio of the frequency of causal connectives to the total number of words	*so*, *thus*, *hence*, *therefore, consequently, on account of this, for this purpose, for, because, in that case, with regard to this*
Relative frequency of adversative connectives (ADC)	The ratio of the frequency of adversative connectives to the total number of words	*yet*; *although*; *only, however*, *but, whereas*, *despite this*, *to tell the truth*, *actually*, *on the contrary, anyway*
Relative frequency of temporal connectives (Temp)	The ratio of the frequency of temporal connectives to the total number of words	*then*, *next*, *afterwards*, *after that*, *subsequently, at the same time, finally*, *at last*, *first…second…*, *until, up to now*
Relative frequency of additive connectives (Add)	The ratio of the frequency of additive connectives to the total number of words	*and, or, nor, neither, moreover, additionally, likewise, on the other hand, in other words, on the other hand*

discourse cohesion and coherence and is currently one of the most widely used and sophisticated instruments for discourse analysis (Graesser et al. 2004; McNamara et al. 2014). It has been widely applied to the analysis and differentiation of texts across genres.

3.3 | Multivariate Analysis

This study adopted a two-stage multivariate analytical framework combining exploratory and confirmatory techniques. In the first stage, correspondence analysis (CA) (Greenacre 2008, 2010;

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Delaere et al. 2012) was employed as an exploratory method to provide a structural overview of the associations among text varieties, genres, and connective categories prior to formal statistical testing. CA maps these multidimensional relationships onto a low-dimensional geometric space, thereby revealing overarching distributional tendencies. In the present study, text variety and genre were combined into a single grouping variable, and the associations between these genre-text variety combinations and the four connective categories were examined. It should be noted that although CA is conventionally applied to contingency tables of raw frequencies, it has also been extended to ratio-scale data, including normalized frequency data that preserve relative distributional structures (Greenacre 2008, 2010), which corresponds to the form of data used in the present study. The CA was conducted in R (R Core Team 2025) using the FactoMineR package, with graphical displays produced via the factoextra package.

In the second stage, linear mixed-effects models were fitted to test the effects of text variety, genre, and their interaction on the four connective measures. This confirmatory method was chosen because the dependent variables were continuous and the data involved non-independent translations derived from the same source texts. Prior to model fitting, the distributional properties of the dependent variables were inspected using Shapiro-Wilk tests and visual diagnostics. Where positive skewness was observed, the log1p transformation was applied to reduce skewness while retaining zero values. The models were fitted with the lmer() function in the lme4 package. In all models, text variety, genre, and their interaction were specified as fixed effects, and source text (TEXTID) was included as a random intercept to account for the non-independence of observations. More complex random-effects structures, such as by-source-text random slopes for text variety, were also considered, but these models proved unidentifiable because the random-effects structure was too complex relative to the available observations. Accordingly, the final analyses were based on a random-intercept model of the following form:

$$\text{CONNECTIVECATEGORY} \sim \text{TEXTVARIETY} * \text{GENRE} + (1|\text{TEXTID}).$$

The significance of the overall fixed effects was evaluated by Type III analysis of variance (ANOVA). Where significant interaction effects were observed, simple effects analyses were conducted to examine differences between text varieties within each genre. Pairwise contrasts were estimated from the estimated marginal means using the emmeans package, with Bonferroni adjustment for multiple comparisons. Model fit was further summarized using marginal and conditional R^2 values and variance-component estimates for random-effects structure.

4 | Results and Discussion

4.1 | Correspondence Analysis

The CA biplot (Figure 1) shows a clear overall structure in the distribution of connective categories across genre-text variety combinations. Dimension 1 accounted for the vast majority of the variance (89.8%), while Dimension 2 contributed a further 9.4%, providing a more limited but still meaningful degree of additional differentiation. Specifically, causal connectives were located mainly in the upper-right quadrant and were most closely associated with originals and human translations of government documents and academic abstracts. By contrast, additive connectives were positioned primarily on the left side of the plot, clustering around the four machine translations of government documents. Adversative and temporal connectives were concentrated in the lower-right quadrant and aligned more closely with the six text varieties of contemporary novels. Machine-translated academic abstracts, meanwhile, were located lower and closer to the origin, and their relatively small contribution suggested a weaker and less coherent pattern than that observed for the other genre-text variety combinations.

Taken together, these results revealed a broad contrast between human-produced and machine-produced language in government documents and academic abstracts, with human-produced language more closely associated with causal connectives and machine-produced language more closely associated with additive connectives. At the same time, the distributional pattern suggested that machine-translated texts exhibited some clustering tendencies, but the extent to which they formed a distinctive profile appeared to be genre-dependent. The following inferential analyses examine whether these exploratory patterns are statistically robust.

4.2 | Modeling of Connective Usage

4.2.1 | Causal Connectives

The linear mixed-effects model fitted for causal connectives converged successfully and showed no singular fit, indicating that it was statistically stable and suitable for inference. Overall, the fixed effects explained 16.3% of the variance (marginal R^2 = 0.163), while the fixed and random effects together accounted for 45.7% (conditional $R^2 = 0.457$). Variance-component estimates further showed that the random-intercept variance for TEXTID was 0.154 (SD = 0.392), relative to a residual variance of 0.284 (SD = 0.533). This suggested that a non-negligible proportion of the variability in causal connective use was associated with between-text differences, thereby supporting the inclusion of TEXTID as a random effect. For the fixed effects, the model showed significant main effects of text variety, $F(5, 775.05) = 24.17$, $p < 0.001$, and genre, $F(2, 204.51) = 10.12$, $p < 0.001$. In addition, the interaction between text variety and genre was also significant, $F(10, 781.07) = 5.32$, $p < 0.001$. These results indicated that the distribution of causal connectives differed significantly across text varieties and genres, and more importantly, that the differences among text varieties were conditioned by genre. Follow-up simple-effects analyses with pairwise comparisons were therefore conducted to further examine these genre-specific patterns of variation.

As shown in Figure 2 and Table 3, significant differences in the use of causal connectives were observed in academic abstracts and government documents, and the patterns across text varieties were similar in these two genres. More specifically, all four machine-translated varieties differed significantly from both human-authored original texts and human translations, with machine translations showing lower frequencies of causal connectives. At the same time, no significant differences were found either between English originals and human translations or between NMTs and LLM-based MTs. In contemporary novels,

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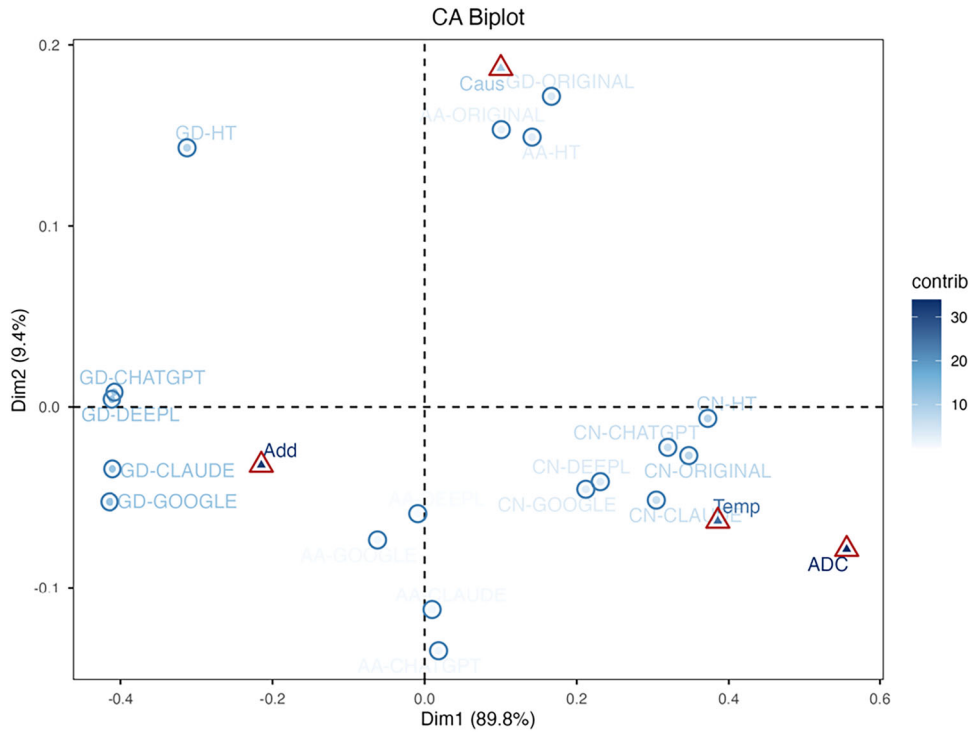

FIGURE 1 | CA biplot of connective usage in text varieties across genres. [Color figure can be viewed at wileyonlinelibrary.com]

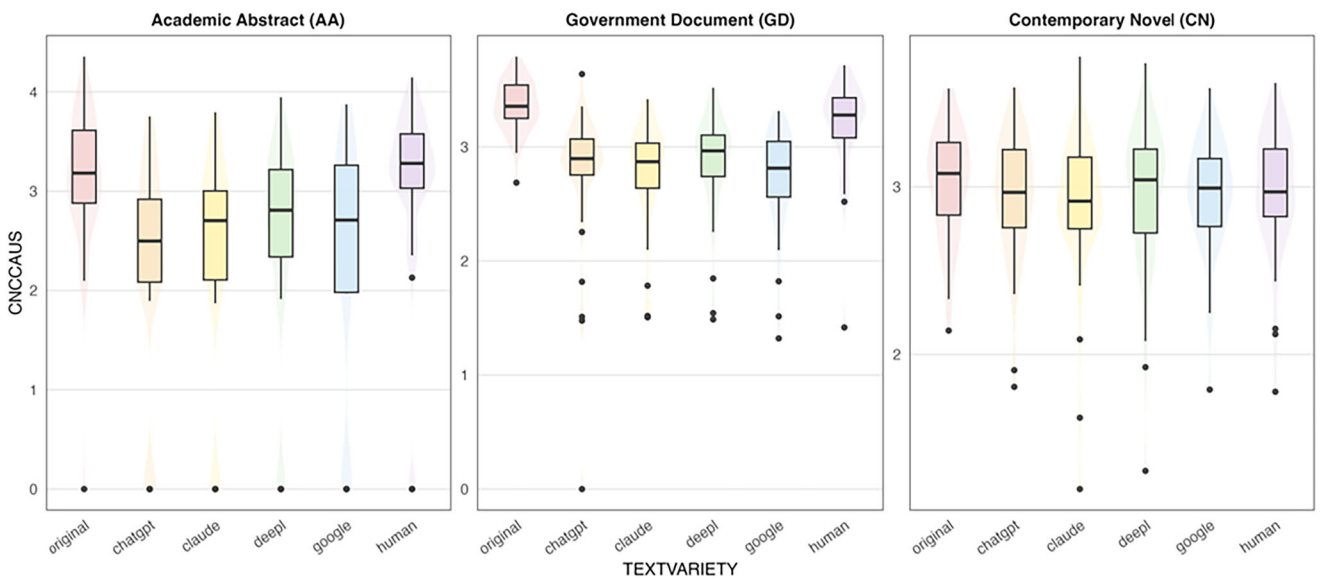

FIGURE 2 | Distribution of causal connectives in text varieties across genres. [Color figure can be viewed at wileyonlinelibrary.com]

by contrast, no statistically significant pairwise differences were found among the six text varieties, even though original texts showed the highest frequency of causal connectives at the descriptive level.

4.2.2 | Adversative and Temporal Connectives

The linear mixed-effects model fitted for adversative connectives converged successfully and did not exhibit singularity. Overall, the fixed effects accounted for approximately 43.2% of the variance (marginal $R^2 = 0.432$), whereas the fixed and random effects together explained about 69.4% (conditional $R^2 = 0.694$). The variance-component estimates indicated that the random-intercept variance associated with TEXTID was 0.329 (SD = 0.573), compared with a residual variance of 0.383 (SD = 0.619). This suggested substantial between-text variability and therefore supported the inclusion of TEXTID as a random intercept. As for the fixed effects, the model revealed a significant main effect of text variety, $F(5, 755.01) = 19.34$, $p < 0.001$, and genre, $F(2, 209.38) = 99.06$, $p < 0.001$. Importantly, the interaction between text variety and genre was also significant, $F(10, 771.96)$

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TABLE 3 | Results of the simple effect analysis for the use of causal connectives.

Connective	Genre	Contrast	Estimate	Standard error	*p*-value
Caus	AA	Original–ChatGPT	0.874	0.106	<0.001
		Original–Claude	0.742	0.106	<0.001
		Original–DeepL	0.583	0.106	<0.001
		Original–Google	0.846	0.106	<0.001
		Chatgpt–Human	−0.817	0.106	<0.001
		Claude–Human	−0.685	0.106	<0.001
		Deepl–Human	−0.526	0.106	<0.001
		Google–Human	−0.789	0.106	<0.001
	GD	Original–ChatGPT	0.525	0.110	<0.001
		Original–Claude	0.533	0.110	<0.001
		Original–DeepL	0.441	0.110	0.001
		Original–Google	0.585	0.110	<0.001
		ChatGPT–Human	−0.417	0.107	0.002
		Claude–Human	−0.425	0.107	0.001
		Deepl–Human	−0.332	0.107	0.028
		Google–Human	−0.477	0.107	<0.001

Note: For reasons of space, only statistically significant pairwise comparisons are displayed.

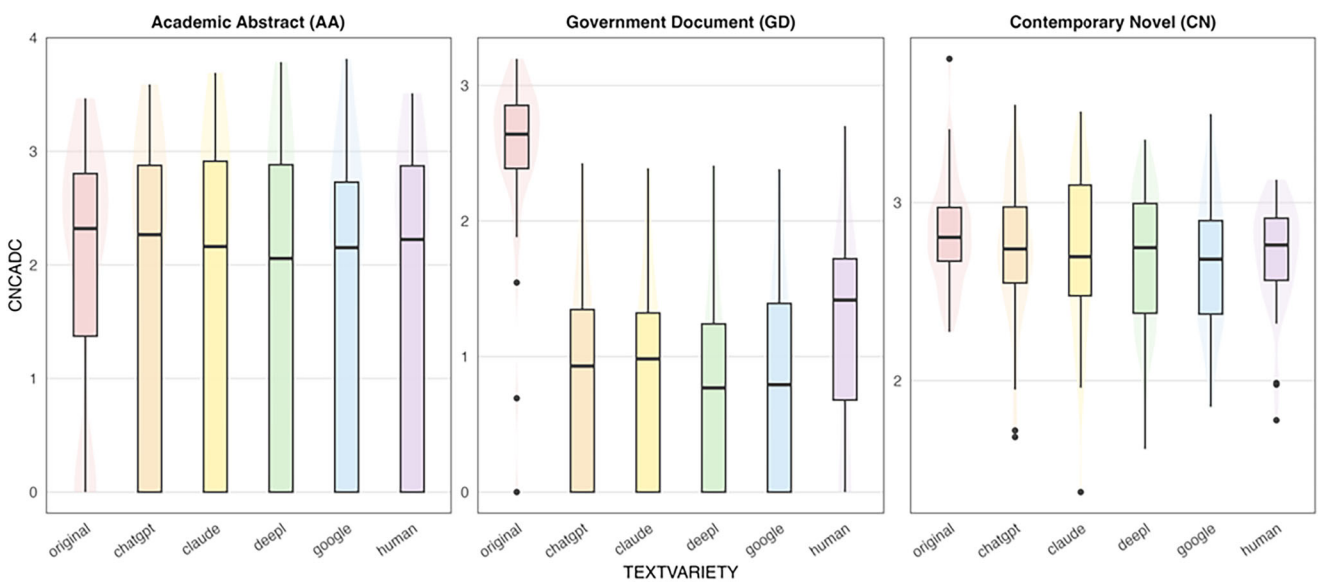

FIGURE 3 | Distribution of adversative connectives in text varieties across genres. [Color figure can be viewed at wileyonlinelibrary.com]

= 13.10, $p < 0.001$. These results indicated that the distributional differences among text varieties were genre-dependent. In light of this significant interaction, follow-up pairwise comparisons were conducted within each genre.

As shown in Figure 3 and Table 4, no significant differences were found among the text varieties in academic abstracts and contemporary novels. Significant differences emerged only in government documents, where both machine translations and human translations showed substantially lower frequencies of adversative connectives than English original texts, reflecting a distinction between translational and non-translational language in this genre. Generally, machine translations and human translations are patterned similarly in government documents. The only exception was a significant difference between DeepL and human translations, but this isolated contrast did not alter the broader distinction between translated and original texts. Moreover, no significant differences were found between NMTs and LLM-based MTs.

The linear mixed-effects model fitted for temporal connectives converged successfully and showed no singular fit. Overall, the

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TABLE 4 | Results of the simple effect analysis for the use of adversative connectives.

Connective	Genre	Contrast	Estimate	Standard error	*p*-value
ADC	GD	Original–Chatgpt	1.645	0.128	<0.001
		Original–Claude	1.622	0.128	<0.001
		Original–Deepl	1.690	0.128	<0.001
		Original–Google	1.618	0.128	<0.001
		Original–Human	1.271	0.128	<0.001
		DeepL–Human	−0.419	0.124	0.011

Note: For reasons of space, only statistically significant pairwise comparisons are displayed.

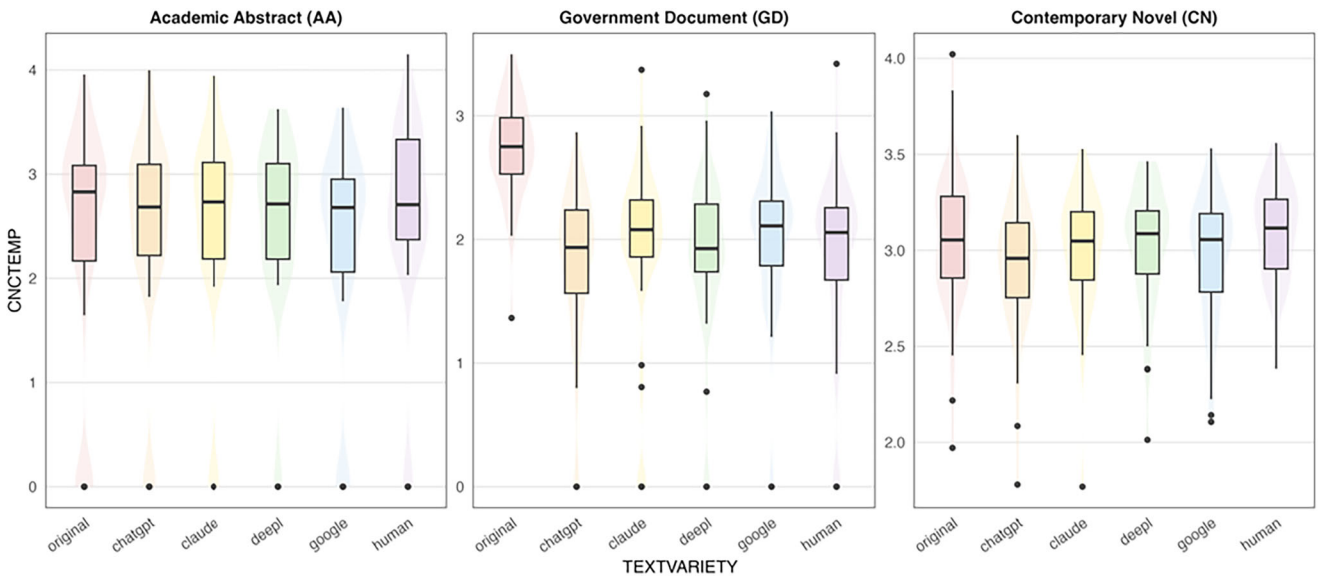

FIGURE 4 | Distribution of temporal connectives in text varieties across genres. [Color figure can be viewed at wileyonlinelibrary.com]

fixed effects accounted for approximately 28.1% of the variance (marginal R^2 = 0.281), while the fixed and random effects together explained 51.7% (conditional R^2 = 0.517). The variance-component estimates showed that the random-intercept variance associated with TEXTID was 0.162 (SD = 0.403), whereas the residual variance was 0.330 (SD = 0.574). This suggested that a meaningful proportion of the variability in temporal connective use was attributable to between-text differences, thereby supporting the inclusion of TEXTID as a random intercept. With regard to the fixed effects, the model revealed significant main effects of text variety, $F(5, 777.05) = 4.46$, $p < 0.001$, and genre, $F(2, 202.19) = 65.29$, $p < 0.001$. The interaction between text variety and genre was also significant, $F(10, 781.19) = 6.63$, $p < 0.001$. Taken together, these results indicated that the use of temporal connectives varied significantly across both text varieties and genres, and that the differences among text varieties were themselves genre-dependent. Follow-up pairwise comparisons were therefore conducted to further examine these genre-specific differences.

As shown in Figure 4 and Table 5, and similar to the pattern observed for adversative connectives, no significant differences among text varieties were found in academic abstracts or contemporary novels. Significant differences emerged only in government documents, where both machine translations and human translations showed substantially lower frequencies of temporal connectives than English original texts, pointing to a distinction between translational and non-translational language in this genre. Moreover, no significant differences were found either between machine translations and human translations, or between NMTs and LLM-based MTs.

4.2.3 | Additive Connectives

The linear mixed-effects model fitted for additive connectives converged successfully and showed no singular fit. The fixed effects accounted for approximately 57.0% of the variance (marginal R^2 = 0.570), while the fixed and random effects together explained 76.9% (conditional R^2 = 0.769). The variance-component estimates showed that the random-intercept variance associated with TEXTID was 0.022 (SD = 0.149), compared with a residual variance of 0.026 (SD = 0.161). This suggested that between-text variability remained non-negligible, thereby justifying the inclusion of TEXTID as a random effect. As for the fixed effects, the model revealed significant main effects of text variety, $F(5, 722.12) = 63.19$, $p < 0.001$, and genre, $F(2, 176.50) = 161.26$, $p < 0.001$. Importantly, the interaction between

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TABLE 5 | Results of the simple effect analysis for the use of temporal connectives.

Connective	Genre	Contrast	Estimate	Standard error	*p*-value
Temp	GD	Original–ChatGPT	0.899	0.118	<0.001
		Original–Claude	0.757	0.118	<0.001
		Original–DeepL	0.831	0.118	<0.001
		Original–Google	0.697	0.118	<0.001
		Original–Human	0.859	0.118	<0.001

Note: For reasons of space, only statistically significant pairwise comparisons are displayed.

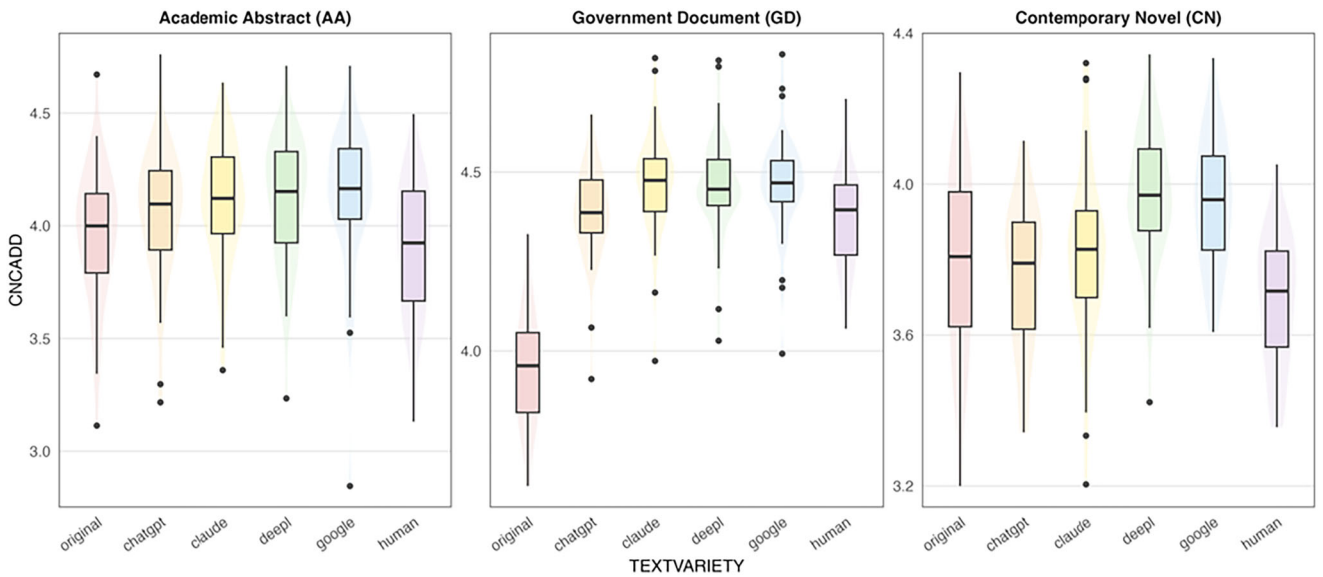

FIGURE 5 | Distribution of additive connectives in text varieties across genres. [Color figure can be viewed at wileyonlinelibrary.com]

text variety and genre was also significant, $F(10, 741.46) = 18.27$, $p < 0.001$. These results indicated that the differences among text varieties varied across genres. In light of this significant interaction, follow-up pairwise comparisons were conducted to examine these genre-specific patterns in greater detail.

As illustrated in Figure 5 and Table 6, distinct patterns emerged across the three genres. In academic abstracts, the four machine-translated varieties showed significantly higher frequencies of additive connectives than both human translations and original texts, whereas no significant difference was found between human translations and originals, nor among the four machine-translated varieties. This pattern pointed to a clear distinction between machine-produced and human-produced language. In government documents, both machine translations and human translations exhibited higher frequencies of additive connectives than original texts. Although Claude also differed significantly from human translations, the overall pattern still pointed primarily to a broader contrast between translational and non-translational language, as well as a pattern of convergence within translated texts. In contemporary novels, the two NMT varieties showed significantly higher frequencies of additive connectives than all other text varieties, whereas no significant differences were observed among the remaining varieties. This finding suggested a particularly distinctive profile for NMT output in this genre.

4.3 | Discussion

Drawing on the results of the correspondence analysis and the linear mixed-effects models, the present study yielded the following main findings. First, a clear distinction emerged between machine-translated language and human-produced language, including both human translations and human-authored original texts, in the use of causal and additive connectives. More specifically, in academic abstracts and government documents, machine-translated texts used significantly fewer causal connectives than human-produced texts, whereas in academic abstracts, machine-translated texts used significantly more additive connectives. Notably, no significant differences were found between human translations and human-authored original texts. This pattern sets MT output apart from both human translations and human-authored original texts. These findings are consistent with earlier observations in related studies. Puurtinen (2003) and Song (2022), for example, showed that connective use did not display a simple overall increase, and that it might vary even across different translations of the same source text. In addition, Jiang

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TABLE 6 | Results of the simple effect analysis for the use of additive connectives.

Connective	Genre	Contrast	Estimate	Standard error	*p*-value
Add	AA	Original–ChatGPT	−0.099	0.032	0.028
		Original–Claude	−0.143	0.032	<0.001
		Original–Deepl	−0.155	0.032	<0.001
		Original–Google	−0.183	0.032	<0.001
		ChatGPT–Human	0.160	0.032	<0.001
		Claude–Human	0.204	0.032	<0.001
		DeepL–Human	0.215	0.032	<0.001
		Google–Human	0.243	0.032	<0.001
	CN	Original–DeepL	−0.180	0.043	0.001
		Original–Google	−0.165	0.043	0.002
		ChatGPT–DeepL	−0.210	0.032	<0.001
		ChatGPT–Google	−0.195	0.032	<0.001
		Claude–DeepL	−0.151	0.032	<0.001
		Claude–Google	−0.136	0.032	<0.001
		DeepL–Human	0.276	0.032	<0.001
		Google–Human	0.261	0.032	<0.001
	GD	Original–ChatGPT	−0.438	0.033	<0.001
		Original–Claude	−0.521	0.033	<0.001
		Original–DeepL	−0.506	0.033	<0.001
		Original–Google	−0.513	0.033	<0.001
		Original–Human	−0.420	0.033	<0.001
		Claude–Human	0.101	0.032	0.027

Note: For reasons of space, only statistically significant pairwise comparisons are displayed.

(2014) found that machine translations of competition texts used more additive conjunctions than human translations, while Han and Jiang (2016) reported a similar tendency in English-Chinese translations of novels, where machine translations overused the additive connective *和* ('and'). Moreover, Jiang and Niu (2022a, 2022b) and Liang and Liu (2023) suggested that MT systems were less likely than human translators to encode deeper semantic relations such as causality and intentionality in an explicit and contextually appropriate manner. Taken together, these findings answer the first research question by showing that machine-translated language was distinguished from human-produced language most clearly in its distribution of causal and additive connectives.

Second, machine translations and human translations, both as varieties of translational language, showed a noticeable tendency to converge in their use of additive, adversative, and temporal connectives in government documents. More specifically, both used significantly fewer adversative and temporal connectives, but significantly more additive connectives, than the original texts. This convergence might partly reflect shared source-text constraints, as indicated by the non-negligible random effects in the models. These patterns are also compatible with earlier claims that translated language might display distinctive probabilistic tendencies (Baker 1993; Toury 2004, 2012; Chesterman 2004, 2016) and resonated with Laviosa's (2002) notion of convergence of translated texts as well. At the same time, the present results suggested that, in government documents, explicitation (Blum-Kulka 1986; Baker 1993) through discourse connectives was realized primarily via additive marking rather than through causal, adversative, or temporal marking. Similar tendencies were also noted in other language pairs and genres. Loock (2020), for instance, found that French machine translations in a news corpus used the additive connective *et* ('and') more frequently than French original texts, while Kuo (2019) reported that machine translations in Chinese Wikipedia overused the connective *和* ('and') relative to Chinese original writing. The above set of findings addresses the second research question by suggesting that machine translations and human translations might converge as varieties of translational language, particularly through the shared overuse of additive connectives and underuse of adversative and temporal connectives in government documents.

Third, despite relying on different AI paradigms, NMTs and LLM-based MTs differed only minimally in connective use. Across most connective categories and genres, no significant differences were observed between them. The only significant difference concerned additive connectives in contemporary novels, where NMT outputs showed higher frequencies than LLM-based MT outputs. This pattern echoes Jiang and Niu's (2022a) observation that Google tended to overuse *and* in literary translation,

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produce what they described as a form of pseudo-coherence. More generally, the present findings suggested that LLM-based systems, despite their larger training data and more advanced architectures, did not differ substantially from NMT systems with respect to the connective measures examined here. In this sense, certain distributional properties of machine-translated language appeared relatively stable across evolving MT paradigms. These results address the third research question by indicating that the shift from NMT to LLM-based MT has not substantially altered the distributional profile of discourse connectives, apart from a limited genre-specific difference in additive connective use.

To recap, the above findings suggest that machine-translated language generally tends to rely more heavily on additive connectives, whereas human-produced texts, especially human-authored original texts, show a stronger preference for causal, adversative, and temporal connectives. One plausible explanation for this pattern concerns the differing semantic and discourse-processing demands associated with these connective types. Compared with additive connectives, causal, adversative, and temporal connectives typically require more fine-grained interpretation of discourse structure, including causal reasoning, contrastive expectation, and event sequencing. This interpretation also resonates with previous research on discourse-level differences between machine and human translations. Hoek et al. (2015), for example, note that machine translation shows less variability than human translation in the rendering of discourse relations, which they relate to differences in discourse interpretation. Likewise, recent work suggests that machine systems remain less successful in handling deeper discourse relations (Jiang and Niu 2022a, 2022b; Liang and Liu 2023; Huang and Cheung 2026). From this perspective, the higher frequencies of causal, adversative, and temporal connectives in human-produced texts may reflect a greater tendency to infer and encode more specific and fine-grained discourse relations, whereas machine systems more often fall back on additive markers as safer, more general, and semantically less committal options.

A further explanation may lie in the mechanisms of machine text generation and the statistical biases of training data. MT systems learn distributional regularities from large-scale corpora and generate output by selecting highly probable continuations. When implicit discourse relations are not sufficiently recoverable from context, they may default to high-frequency and semantically general connectives such as the additive connective *and* (Halliday and Hasan, 1976; Rysová 2017), a tendency that is especially plausible in end-to-end NMT systems operating over limited contextual spans. This tendency may be further reinforced by algorithmic bias, which amplifies high-frequency linguistic forms while attenuating lower-frequency alternatives (Vanmassenhove et al. 2019, Vanmassenhove et al. 2021). Taken together, these factors may contribute to the overuse of additive connectives in machine translations and the relative underrepresentation of the more semantically specific relations required for causal, adversative, and temporal marking. The following example provides a concrete illustration of this tendency.

Source text: 我们加大扶贫力度, 贫困地区的生产生活条件得到明显改善。(2010 Government Work Report)

Literal gloss: We intensified poverty alleviation efforts; production and living conditions in poor areas improved significantly.

DeepL: We have stepped up our efforts to alleviate poverty, and production and living conditions in poor areas have been significantly improved.

Google Translate: We have stepped up poverty alleviation efforts, and production and living conditions in poor areas have been significantly improved.

ChatGPT: We intensified poverty alleviation efforts, significantly improving production and living conditions in impoverished areas.

Claude: We increased our efforts to alleviate poverty, and the production and living conditions in poor areas were significantly improved.

Human: We also intensified our efforts to fight poverty. As a result, working and living conditions notably improved in poverty-stricken areas.

Finally, the present findings indicate that these patterns should not be treated as uniform across all genres. Rather, the extent to which machine-generated texts cluster around additive connectives, and human-produced texts around causal, adversative, and temporal connectives, appears to be strongly genre-dependent. This interpretation is in line with recent evidence that register variation can strongly condition cohesive and coherent patterning across translated and non-translated texts (Zufferey and Degand 2024; Li and Gao 2025). The contrast identified here is therefore best understood not as an absolute opposition between human and machine language, but as a genre-sensitive distributional tendency in the signaling of discourse relations. It also supports a more cautious theoretical position, in line with Chesterman (2004, 2016) and Toury (2004, 2012), according to which the linguistic properties of translated language are better understood as tendencies rather than universals. In this respect, the findings answer the fourth research question by demonstrating that the linguistic profile of machine-translated language should be understood as a genre-conditioned tendency rather than a genre-independent universal.

5 | Conclusion

By integrating exploratory correspondence analysis with confirmatory linear mixed-effects modeling, this study examined the discourse-level features of machine-translated language, using discourse connectives as key indicators. Through comparisons with human translations and target-language original texts, the study yielded several main findings. Overall, the findings showed that machine-translated language differed systematically from human-produced language in discourse connective use, but that this difference was strongly genre-dependent. In general, machine-translated texts tended to rely more heavily on additive connectives, whereas human-produced texts, especially human-authored original texts, showed a stronger preference for causal, adversative, and temporal connectives in academic abstracts and/or government documents. At the same time, machine

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translations and human translations converged in government documents, where both differed from human-authored original texts in similar ways. Moreover, NMT and LLM-based MT exhibited only limited differences, suggesting a degree of stability in connective preferences across different AI paradigms.

These findings have both theoretical and practical implications. Theoretically, they suggest that machine-translated language is better understood not merely as a technical by-product of automated processing, but as a genre-sensitive translational variety with relatively stable discourse tendencies across MT paradigms. In this way, the study refines current discussions of translational varieties and shows that discourse connectives provide a useful entry point for examining how discourse relations are differently encoded in human- and machine-mediated translation. Practically, the findings highlight the need for translators, post-editors, and trainees to attend more closely to connective use in MT output, especially where additive connectives may be overused and causal, adversative, or temporal relations may be underrepresented. Such attention should also be genre-sensitive. For example, in machine-translated government documents, additive marking may require closer scrutiny, whereas in machine-translated academic abstracts causal relations may need to be checked more carefully, and in NMT-translated fictional texts additive connective use should be evaluated with regard to stylistic effects. The study therefore offers implications for more genre- and discourse-sensitive post-editing and for the development of machine translation literacy in professional and pedagogical contexts.

Several limitations should also be acknowledged. First, this study focused only on discourse connectives and therefore captured only one dimension of discourse organization. Other aspects of cohesion and coherence, such as lexical overlap, co-reference, and broader semantic connectedness, also warrant investigation to provide a broader account of machine-translated language as a translational variety. Second, although academic abstracts were treated in this study as a distinct and bounded academic genre, their compressed and formulaic character means that they cannot be assumed to represent academic writing as a whole. Future research may therefore extend the analysis to fuller forms of academic prose in order to test whether the patterns identified here remain stable in broader academic discourse.

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Ethics Statement

This research did not require ethical approval because it did not involve human participants, animal subjects, or any ethically sensitive data.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data will be made available on request.

Peer Review

For transparency, the peer review documents associated with this article are available at https://doi.org/10.1111/ijal.70282.

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