

AI Translation vs. Human Originality: A Corpus-Based Comparative Analysis of Academic Persuasiveness in Scientific Literature

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Abstract: Based on the Toulmin argumentation model and corpus quantitative analysis, this study compares the academic persuasive features of Chinese original, AI-translated, and English original scientific texts. The results show that AI translation can reproduce the basic “claim-evidence” framework but lacks higher-order argumentative elements, with mechanical conversion of logical relations and imbalanced rhetorical strategies. Cross-cultural comparison reveals that Chinese academic writing adopts “explicit persuasion” while English uses “implicit persuasion”, and AI fails to adapt to such differences, reflecting its core shortcoming in argumentative reconstruction rather than language conversion. This study verifies the Toulmin model’s effectiveness in cross-linguistic analysis, provides empirical implications for AI technology optimization, scholar usage strategies, and academic translation industry development, and offers a path to improve academic communication quality in the technological innovation context.

Keywords: AI translation; Academic persuasiveness; Corpus-based research; Scientific literature; Argumentation analysis

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1. Introduction

AI-assisted translation (AI translation) has become essential in international academic exchanges, bridging cross-linguistic scientific knowledge. Scientific literature conveys both research findings and academic persuasiveness, critical for global recognition^[1]. Through structured argumentation and rhetorical strategies, academic texts demonstrate rigor that enables effective knowledge transfer^[2].

Despite its prevalence, AI translation evaluation is limited. Current assessments focus on surface features like fluency and terminological accuracy, often overlooking persuasiveness. Translations may be linguistically correct yet fail to maintain logical rigor, reducing their scholarly value. Academic persuasiveness depends on argumentative integrity, logical coherence, and appropriate rhetorical strategies, all vital for cross-linguistic

dissemination^[3]. Yet most studies emphasize accuracy or efficiency, neglecting how AI reconstructs argumentative structures, limiting understanding of AI's capabilities and its impact on Chinese research abroad.

This study addresses the gap using a trilingual parallel corpus, combining corpus linguistics and contrastive rhetoric. It examines AI's strengths and limitations in argumentation reconstruction and offers empirical guidance for optimization, enhancing cross-linguistic academic communication. To explore persuasiveness differences between AI-translated and human-original texts, three research questions are proposed: (1) How are argument units distributed in AI translations compared with Chinese and English originals? (2) How does AI transmit logical relations, and how does its use of connectives differ from human texts? (3) How do rhetorical features differ between AI translations and human originals, and how do they affect persuasiveness?

The methodological framework integrates three principles. Corpus paralleling constructs three parallel corpora under strict controls for discipline, journal tier, and text type. Multi-dimensional analysis examines argument units, logical relations, and rhetorical features from micro to macro. Quantitative–qualitative integration combines statistical validation with discourse-based interpretation, enhancing rigor and explanatory depth.

2. Literature review

2.1. AI translation quality assessment

Research on AI translation quality assessment has developed two main paradigms: algorithm-based automatic evaluation and human-based subjective evaluation. Automatic metrics such as BLEU, TER, and METEOR primarily measure lexical and syntactic overlap with reference texts. While effective for general texts, they fail to capture deep structural features of academic texts, such as argumentation integrity and rhetorical appropriateness^[4]. Human-based evaluation emphasizes fluency, terminological consistency, and stylistic fit but lacks a systematic framework to assess the core functional attribute of academic texts—persuasiveness^[5]. Most studies treat translation as a language conversion process, overlooking its role in transmitting academic argumentation, revealing a notable blind spot in evaluating AI translation's academic applicability.

2.2. Academic persuasiveness in scientific literature

In English for science and technology (EST) research, Hyland's (2005) academic discourse analysis framework provides a foundational basis for studying academic persuasiveness^[6]. The framework emphasizes two key functions: guidance, helping readers follow the argument through logical markers and structural design, and engagement, creating dialogue with the academic community via rhetorical strategies such as hedges and self-mentions. Subsequent studies have refined persuasiveness into three levels^[7]: micro-level argument units (claim-evidence-warrant integrity), meso-level logical relations (semantic relations between propositions via connectives), and macro-level rhetorical features (appropriate use of hedges, self-mentions, and other discourse markers). While comprehensive, these analyses mostly focus on single-language texts, lacking a systematic investigation of cross-linguistic transmission or AI translation performance.

2.3. Corpus-based comparative research on academic translation

Corpus linguistics offers a rigorous empirical method for comparing academic translations. Existing studies mainly contrast linguistic features, such as lexical density and syntactic complexity, between translated and original texts^[8]. In Chinese-English translation research, scholars have examined differences in connectives and hedges between Chinese-English translated and English original papers, but these studies largely focus on human translations,

rarely addressing AI translations, which are increasingly prevalent ^[9]. Moreover, corpus studies seldom integrate the three core dimensions of academic persuasiveness, limiting insights into how AI translation transmits academic argumentation.

In summary, current research exhibits three limitations: (1) AI translation evaluation emphasizes surface linguistic features, neglecting deep academic persuasiveness; (2) studies of academic persuasiveness are mostly single-language, lacking cross-linguistic comparison; (3) corpus-based translation research rarely involves AI and lacks a comprehensive framework. This study addresses these gaps by constructing a trilingual parallel corpus and applying a multidimensional analysis framework, providing an important supplement to existing research.

3. Data and method

3.1. Corpus construction

The parallel corpora constructed in this study are composed exclusively of academic research articles in the field of automotive engineering to ensure thematic consistency and analytical comparability. The specific composition of the corpora is presented in **Table 1**.

Table 1. Description of the parallel corpora in this study

| Corpus type | Source journal/Generation method | Number of texts | Corpus size (words/characters) | Core function |
|-----------------------------|---|-----------------|--------------------------------|---|
| Corpus C (Chinese Original) | Chinese Journal <i>Automotive Engineering</i> | 15 | Approx. 29500 | Benchmark control: reflecting the argumentative norms of native Chinese academic writing |
| Corpus T (AI-translated) | Translated from Corpus C into English by DeepSeek | 15 | Approx. 16500 | Core analysis object: reflecting the argumentative conversion effect of AI academic translation |
| Corpus E (English Original) | English-language journals published by Elsevier | 15 | Approx. 24800 | Target reference: representing the argumentative conventions of English academic writing |

All texts included in the three corpora are core journal articles published within the past five years. The selected papers cover representative subfields such as new energy technologies and intelligent driving systems, and exhibit complete research designs and well-structured argumentative patterns, thereby meeting standard academic writing conventions.

Corpus T was generated using the DeepSeek-V3.1 translation system. The translation prompt was specified as: “Translate the following Chinese into English in an academic paper style.” The translated texts subsequently underwent light manual proofreading to eliminate overt grammatical errors, without altering argumentative content, so as to ensure the validity of subsequent analyses.

3.2. Index extraction

Drawing on the Toulmin model of argumentation and the communicative functions of academic discourse, this study extracts core analytical indicators from three dimensions: argumentative units, logical relationships, and rhetorical features.

3.2.1. Indicators of argumentative units

With respect to argumentative units, the analysis focuses on five core components of the Toulmin model and examines their explicit realizations in academic texts ^[10]. Claims are treated as overt statements of academic propositions, including research conclusions and theoretical hypotheses, and are annotated in terms of both frequency and clarity, the latter operationalized through the presence of explicit stance-marking expressions. Evidence refers to the empirical support provided for claims, encompassing experimental data, factual observations, and references to prior research; corresponding indicators include evidence type distribution and evidence density. Warrants are identified as the logical mechanisms linking claims and evidence, typically realized through causal reasoning or theoretical justification, and are analyzed with respect to both frequency and degree of explicitness. Rebuttals are defined as responses to potential counterarguments or exceptional cases and are evaluated based on their frequency and argumentative relevance. Qualifiers denote modal expressions that delimit the scope or certainty of claims, such as *may* or *partly*, and are analyzed in terms of usage frequency and type distribution.

Collectively, these indicators reflect the completeness and rational organization of argumentative structures and constitute core dimensions for assessing academic persuasiveness. It should be noted that backing, understood as generalized external authority supporting warrants (e.g., universal principles, industry standards, or foundational theories), occurs infrequently in scientific and technical writing and is therefore excluded from the present analysis.

3.2.2. Indicators of logical relationships

Logical relationships are examined to capture how argumentative units are connected to form coherent argumentative chains. These relationships reflect the internal organization and progression of academic argumentation and are operationalized through four categories: support, contrast, causality, and concession. Quantifying these relations allows for systematic comparison of argumentative coherence and structural preferences across the three corpora.

3.2.3. Indicators of rhetorical features

Rhetorical features are analyzed to account for discourse-level strategies that contribute to argumentative effectiveness in academic writing. Particular attention is given to metadiscourse resources, including self-mention (e.g., *this paper*, *we*), reader engagement markers (e.g., *as noted above*), and attitude markers (e.g., *importantly*, *significantly*). In addition, evidence presentation strategies—such as specific data reporting, case-based illustration, and citation of authoritative sources—are examined, with frequency serving as the primary analytical indicator. Tone adjustment strategies, including affirmative, speculative, and hedging expressions, are also analyzed through their distributional patterns. Together, these rhetorical indicators reveal how academic texts deploy linguistic and discourse strategies to enhance persuasiveness and provide a basis for evaluating the communicative performance of AI-translated academic writing.

3.3. Data preparation and coding

Prior to analysis, all corpora undergo standardized preprocessing procedures. Corpus C and Corpus E retain core argumentative sections, including titles, abstracts, introductions, main argumentative bodies, and conclusions, while non-argumentative elements such as figures, tables, formulas, and reference lists are excluded. Corpus T is aligned with Corpus C at the sentence level to ensure one-to-one correspondence of argumentative units. All texts

are encoded in UTF-8 format and processed using AntConc 3.5.8, with Jieba applied for Chinese segmentation and NLTK for English tokenization.

Argumentative annotation is conducted based on a revised five-element Toulmin framework consisting of claim, evidence, warrant, rebuttal, and qualifier. Sentences or sentence clusters serve as the basic annotation units to ensure correspondence between form and argumentative function. Three annotation dimensions are distinguished: argumentative element type, logical relationship category, and rhetorical feature. A double-annotation with cross-validation procedure is adopted, involving two annotators with expertise in linguistics and automotive engineering. Inter-annotator reliability is assessed using Cohen's Kappa, with values exceeding 0.85. Discrepancies are resolved through discussion to achieve consensus.

Statistical analysis combines descriptive and inferential methods and is conducted using R 4.3.0. Descriptive statistics include raw frequencies, standardized frequencies per 100 sentences, and proportional distributions of argumentative units, logical relationships, and rhetorical features across the three corpora. Inferential analysis employs chi-square tests to examine cross-corpus distributional differences and one-way analysis of variance (ANOVA) to assess the effects of corpus type on argumentative feature frequency, with Bonferroni-adjusted post-hoc comparisons. Supplementary correlation analyses are conducted among key argumentative indicators to support subsequent qualitative interpretation.

4. Results

This section presents the comparative analysis results of argumentative features across three corpora: Chinese Original (C-Corpus), AI-translated (T-Corpus), and English Original (E-Corpus). Based on the Toulmin model, the analysis focused on argumentative units, logical relations, and rhetorical features. All data were standardized to "frequency per 100 sentences"; descriptive statistics characterized feature distributions, and chi-square tests (via R 4.3.0) verified cross-corpus difference significance ($P < 0.05$ =significant, $P < 0.01$ =highly significant, $P < 0.001$ =extremely significant).

4.1. Descriptive statistical results

Table 2 presents the descriptive statistics for the three corpora. The C-Corpus, T-Corpus, and E-Corpus contain 468, 692, and 999 sentences, respectively, providing a sufficient empirical basis for analysis.

In terms of argumentative units, claims and evidence dominate all three corpora, with frequencies exceeding 34 occurrences per 100 sentences. The T-Corpus exhibits the highest claim frequency (42.63), whereas the C-Corpus shows the highest frequency of rebuttals (18.80), markedly exceeding those in the T-Corpus (12.28) and E-Corpus (7.61). The use of warrants increases progressively from the C-Corpus (9.83) to the T-Corpus (11.13) and the E-Corpus (12.41). Qualifiers are infrequent across all corpora, with frequencies not exceeding 0.64 per 100 sentences.

Regarding logical relationships, support relations predominate across corpora, following the pattern E-Corpus (68.07) > T-Corpus (59.83) > C-Corpus (47.01). The C-Corpus displays the highest frequencies of causal (24.57) and concession (9.83) relations. Contrast relations occur at identical frequencies in the C-Corpus and T-Corpus (15.17), both substantially higher than in the E-Corpus (9.91).

In terms of rhetorical features, boosters are most frequent in the C-Corpus (51.71), whereas the E-Corpus exhibits higher frequencies of hedges (19.12), conjunctions (42.44), and references (35.04). The T-Corpus shows

the lowest frequency of conjunctions (26.16), while hedge usage is comparable to that of the C-Corpus (14.31 vs. 14.53).

Table 2. Descriptive statistical results of the corpora

| Analytical dimension | Specific category | C-Corpus (Chinese original) | T-Corpus (AI-translated) | E-Corpus (English original) |
|--------------------------|--------------------|--------------------------------|-----------------------------|--------------------------------|
| Corpus basic information | Total Sentences | 468 | 692 | 999 |
| Argumentative units | Claim (C) | 38.89 | 42.63 | 40.14 |
| | Evidence (E) | 37.18 | 34.39 | 37.34 |
| | Rebuttal (R) | 18.80 | 12.28 | 7.61 |
| | Warrant (W) | 9.83 | 11.13 | 12.41 |
| | Qualifier (Q) | 0.64 | 0.43 | 0.50 |
| Logical relations | Support (S) | 47.01 | 59.83 | 68.07 |
| | Causality (Ca) | 24.57 | 19.08 | 15.82 |
| | Contrast (Ct) | 15.17 | 15.17 | 9.91 |
| | Concession (Cn) | 9.83 | 4.77 | 4.10 |
| Rhetorical features | Boosters (B) | 51.71 | 38.29 | 39.14 |
| | Hedges (H) | 14.53 | 14.31 | 19.12 |
| | Conjunctions (Con) | 34.40 | 26.16 | 42.44 |
| | References (Ref) | 31.41 | 24.57 | 35.04 |

Note: All data are standardized to frequency per 100 sentences for cross-corpus comparability. Statistical analyses were conducted using R 4.3.0

4.2. Inferential statistical results

Chi-square tests are conducted to assess the statistical significance of cross-corpus differences, with detailed results reported in **Table 3**. For argumentative units, no significant differences are observed for claims, evidence, or qualifiers. In contrast, warrants show highly significant differences ($\chi^2 = 10.24$, $P = 0.006$), following the pattern E-Corpus > T-Corpus > C-Corpus, while rebuttals exhibit very high significance ($\chi^2 = 95.42$, $P < 0.001$), following the reverse order C-Corpus > T-Corpus > E-Corpus.

All categories of logical relationships reach very high levels of significance ($\chi^2 \geq 24.79$, $P < 0.001$). Support relations are most frequent in the E-Corpus, followed by the T-Corpus and C-Corpus. Causal relations are most prevalent in the C-Corpus and decrease progressively in the T-Corpus and E-Corpus. Concession relations follow the pattern C-Corpus > E-Corpus > T-Corpus, while contrast relations occur at identical frequencies in the C-Corpus and T-Corpus, both exceeding those in the E-Corpus.

All rhetorical features also demonstrate very high significance ($\chi^2 \geq 25.63$, $P < 0.001$). Boosters are most frequent in the C-Corpus, followed by the E-Corpus and T-Corpus. Hedges are more prevalent in the E-Corpus, whereas the C-Corpus and T-Corpus exhibit comparable frequencies. Both conjunctions and references follow the pattern E-Corpus > C-Corpus > T-Corpus.

Table 3. Summary of Chi-square test results for argumentative features across three corpora

| Analytical dimension | Specific category | Chi-square value | <i>P</i> -value | Statistical significance | Difference ranking |
|----------------------|-------------------|------------------|-----------------|--------------------------|--------------------------------|
| Argumentative units | Claim | 4.27 | 0.118 | Not significant | — |
| | Evidence | 4.65 | 0.098 | Not significant | — |
| | Rebuttal | 95.42 | <0.001 | Extremely significant | C-Corpus > T-Corpus > E-Corpus |
| | Warrant | 10.24 | 0.006 | Highly significant | E-Corpus > T-Corpus > C-Corpus |
| | Qualifier | 1.07 | 0.586 | Not significant | — |
| Logical relations | Support | 147.12 | <0.001 | Extremely significant | E-Corpus > T-Corpus > C-Corpus |
| | Causal | 38.75 | <0.001 | Extremely significant | C-Corpus > T-Corpus > E-Corpus |
| | Contrast | 24.79 | <0.001 | Extremely significant | C-Corpus = T-Corpus > E-Corpus |
| | Concession | 45.23 | <0.001 | Extremely significant | C-Corpus > E-Corpus > T-Corpus |
| Rhetorical features | Booster | 67.41 | <0.001 | Extremely significant | C-Corpus > E-Corpus > T-Corpus |
| | Hedge | 25.63 | <0.001 | Extremely significant | E-Corpus > C-Corpus ≈ T-Corpus |
| | Conjunction | 87.13 | <0.001 | Extremely significant | E-Corpus > C-Corpus > T-Corpus |
| | Reference | 45.89 | <0.001 | Extremely significant | E-Corpus > C-Corpus > T-Corpus |

Notes: 1. Significance levels: $P < 0.05$ =significant, $P < 0.01$ =highly significant, $P < 0.001$ =extremely significant; 2. “C-Corpus ≈ T-Corpus” indicates no substantial statistical difference

Overall, the results indicate distinct argumentative profiles across the three corpora. The T-Corpus consistently occupies an intermediate position between the C-Corpus and E-Corpus, suggesting partial adaptation to English academic conventions while retaining certain source-language argumentative features.

5. Discussion and conclusion

5.1. Discussion

5.1.1. Argumentative persuasiveness in AI-assisted academic translation

The quantitative analysis based on the Toulmin model reveals a distinctive pattern in AI-assisted academic translation: while AI-generated texts demonstrate a high degree of formal alignment with conventional academic structures, their adaptation at higher levels of argumentative persuasiveness remains incomplete. The absence of significant differences in the frequency of claims and evidence across corpora suggests that large language models have acquired core features of the academic register and are capable of reproducing the basic claim–evidence framework of scientific discourse. This finding is consistent with previous research indicating that contemporary AI systems perform well in surface-level academic conventions.

However, differences emerge with respect to higher-order argumentative components. The lower frequency of rebuttals in the AI-translated corpus compared with the Chinese originals, together with the reduced use of warrants relative to English originals, indicates limited engagement with the dialectical depth characteristic of expert academic argumentation. Rather than reflecting isolated deficiencies, these patterns suggest that AI translation currently prioritizes propositional transfer over the reconstruction of argumentative reasoning, particularly in areas requiring evaluative judgment or anticipatory engagement with counterarguments.

Differences in logical relationships further illustrate these constraints. Chinese original texts exhibit a stronger

preference for causal and concessive relations, whereas English originals rely more heavily on support relations to advance arguments incrementally. Although the AI-translated texts approximate English patterns in their increased use of support relations, they continue to reproduce causal and concessive structures inherited from the source texts, indicating partial rather than full adaptation to target-language argumentative conventions. The relatively low frequency of conjunctions in the AI-translated corpus further suggests limited sensitivity to implicit cohesive mechanisms, which may affect the overall coherence of argumentative progression.

Rhetorical feature distribution highlights additional areas of divergence. Chinese originals favor explicit stance-taking through frequent use of boosters, while English originals display a more balanced use of boosters and hedges to project caution and disciplinary alignment. The AI-translated texts exhibit a moderated use of boosters but do not fully incorporate hedging strategies or dense referencing practices, which may weaken the perceived credibility and interpersonal positioning of the academic voice. These patterns point to the challenges AI systems face in modeling the interpersonal and community-oriented dimensions of academic discourse.

5.1.2. Cross-linguistic variation in persuasive modes

The comparative results confirm systematic differences between Chinese and English academic writing in terms of persuasive orientation. Chinese academic texts tend to adopt a more explicit persuasive mode, characterized by frequent rebuttals, causal reasoning, and assertive stance marking, whereas English academic writing favors an implicit mode that emphasizes warrants, support relations, hedging, and dense cohesive devices ^[11]. These differences reflect divergent academic traditions and rhetorical preferences, with Chinese writing often structured around a problem–resolution logic and English writing exhibiting a more linear progression from evidence to reasoning and conclusion.

The AI-translated texts consistently display intermediate characteristics between the two original corpora. While certain source-language persuasive features are attenuated, target-language norms are not fully realized. This intermediate positioning suggests that AI-assisted academic translation operates as a form of partial rhetorical mediation rather than complete argumentative reconstruction. The findings align with previous scholarship emphasizing that effective academic translation requires adaptation to discourse conventions at the level of argumentation, not merely linguistic equivalence.

5.1.3. Implications for AI-assisted academic writing and translation practice

The results suggest that further development of AI-assisted academic translation should move beyond grammatical accuracy and terminological consistency toward enhanced rhetorical and argumentative sensitivity. One potential direction involves incorporating discourse-level training data that explicitly encodes cross-linguistic differences in argumentative organization and logical progression. Additionally, targeted modeling of warrants, hedging strategies, and cohesive devices may help improve AI performance in reconstructing academic argumentation.

From a practical perspective, AI-generated translations may be most effectively positioned as advanced drafts rather than final products. Human intervention remains crucial in refining argumentative coherence, calibrating rhetorical stance, and strengthening evidential support. A collaborative workflow in which AI systems handle initial language transfer and structural drafting, while human experts focus on argumentative optimization and discourse alignment, may offer a balanced approach to efficiency and quality in academic translation.

5.2. Conclusion

Based on a corpus-based quantitative analysis guided by the Toulmin model, this study compared argumentative features across Chinese original texts, AI-translated texts, and English original academic writing in the field of automotive engineering. The findings indicate that AI translations successfully reproduce core academic structures, particularly the claim–evidence framework, but exhibit limitations in higher-order argumentative elements such as warrants, rebuttals, and cohesive rhetorical strategies. As a result, AI-translated texts display formal similarity to English academic writing while differing in argumentative depth and persuasive orientation.

The study further demonstrates that AI translations occupy an intermediate position between Chinese and English academic conventions, reflecting partial adaptation rather than full alignment with target-language norms. These findings underscore the importance of argumentative reconstruction in academic translation and highlight the value of integrating discourse-analytic perspectives into evaluations of AI-assisted writing. By empirically validating the applicability of the Toulmin model in cross-linguistic corpus analysis, this study contributes to a more nuanced understanding of AI's role in academic communication and provides a foundation for future research on improving AI-supported academic writing and translation practices.

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References

- [1] Mohamed YA, Khanan A, Bashir M, et al., 2024, The Impact of Artificial Intelligence on Language Translation: A Review. *IEEE Access*, 2024(12): 25553–25579.
- [2] Koutsantoni D, 2006, Rhetorical Strategies in Engineering Research Articles and Research Theses: Advanced Academic Literacy and Relations of Power. *Journal of English for Academic Purposes*, 5(1): 19–36.
- [3] Martín P, Pérez IKL, 2014, Convincing Peers of the Value of One's Research: A Genre Analysis of Rhetorical Promotion in Academic Texts. *English for Specific Purposes*, 2014(34): 1–13.
- [4] Hyland K, Jiang FK, 2018, "In this Paper We Suggest": Changing Patterns of Disciplinary Metadiscourse. *English for Specific Purposes*, 2018(51): 18–30.
- [5] Chatzikoumi E, 2020, How to Evaluate Machine Translation: A Review of Automated and Human Metrics. *Natural Language Engineering*, 26(2): 137–161.
- [6] Hyland K, 2005, Stance and Engagement: A Model of Interaction in Academic Discourse. *Discourse Studies*, 7(2): 173–192.
- [7] Swales JM, Feak CB, 2004, *Academic Writing for Graduate Students: Essential Tasks and Skills* (Vol. 1). University of Michigan Press, Michigan.
- [8] Baker M, 2019, Corpus Linguistics and Translation Studies: Implications and Applications, in *Researching*

Translation in the Age of Technology and Global Conflict. Routledge, London, 9–24.

- [9] Li ZJ, 2021, A Comparative Study of Lexical and Syntactic Features in Chinese and English Journal Article Titles in the Social Sciences. *Journal of Huaqiao University*, 2021(2): 154–164.
- [10] Toulmin SE, 2003, *The Uses of Argument*. Cambridge University Press, Cambridge.
- [11] Wang J, Wang Y, 2002, Redundancy in Chinese-English Translation from the Perspective of Information Theory. *Chinese Science & Technology Translators*, 2002(4): 1–4 + 12.

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