Multidisciplinary Journal for Advance Research (MJFAR)
ISSN: XXXX-XXXX | e–ISSN: XXXX-XXXX
DOI: 10.20448/under process

How Artificial Intelligence Is Reshaping the Korean-to-English Translation Job Market: A Qualitative Document Analysis

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Abstract: Advances in neural machine translation and large language models (LLMs) are changing how Korean-to-English (KO–EN) translation work is organised, priced, and valued. This qualitative study asks how artificial intelligence (AI) is reshaping the KO–EN translation job market. Using a document-based design, eleven Korea-focused and industry documents published between 2016 and 2026 (news reports, interviews, an industry market report, and scholarly and technical studies) were analysed through reflexive thematic analysis and interpreted against translation-studies and labour-economics scholarship. Six themes emerged: automation of routine text, post-editing as the dominant workflow, polarisation toward high-stakes expertise, contested authorship in literary translation, precarity and pricing pressure, and adaptive role redefinition. Official statistics show that the number of registered translation firms and workers in Korea grew between 2020 and 2023, yet average firm size fell, a pattern consistent with fragmentation rather than contraction. The findings suggest that AI is displacing tasks more than occupations, and that its effects are distributed unevenly across market tiers. Implications for translator training, procurement, and freelancer protection are discussed, together with directions for primary interview research.

Keywords: artificial intelligence, machine translation, Korean–English translation, post-editing, translation labour market, qualitative research, thematic analysis.

Article info: Received 02 January 2026 | revised 17 February 2026 | accepted 03 April 2026 | published 21 May 2026, Vol. 1, Issue No. 1

INTRODUCTION

Translation has long been one of the first professional services touched by language technology (Cronin, 2013; O'Hagan, 2020). The shift from statistical to neural machine translation (NMT) after the Transformer architecture (Vaswani et al., 2017) improved fluency and reduced post-editing effort (Castilho et al., 2017; Toral et al., 2018), and general-purpose large language models (LLMs) now translate competitively across many language pairs (Hendy et al., 2023; Jiao et al., 2023). The commercial consequences are visible. Nimdzi Insights (2025) estimated the global language-services industry at USD 71.7 billion in 2024 and reported that machine translation (MT) and post-editing were among the main sources of revenue growth, even as price pressure became a leading business challenge for providers.

Korean-to-English (KO–EN) translation is a revealing case. Korean and English differ sharply in syntax, morphology, and the encoding of social relations (Brown, 2011; Sohn, 1999), which historically made the pair difficult for automated systems. Commercial NMT reached the Korean market in late 2016, when Naver's Papago and Google Translate adopted neural methods within weeks of each other (Yoon, n.d.), and

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recent comparisons find that LLMs can deliver high-quality KO–EN output (Baek et al., 2024). At the same time, global interest in Korean content has raised the demand for skilled translators, particularly in literature (Jung, 2026b). Whether AI is eroding, reorganising, or expanding the KO–EN job market is therefore an open and practically important question.

Existing scholarship on automation in translation is largely international in scope (Pym & Torres-Simón, 2021; Vieira et al., 2021), while Korea-specific evidence is dispersed across journalism, policy statements, and short technical papers. No study has yet drawn these accounts together to examine how AI is reshaping the KO–EN translation labour market. This article addresses that gap through a qualitative document analysis guided by three research questions, presented after the literature review. It contributes (a) a thematic account of how AI is changing KO–EN translation work, (b) a task-based interpretation that distinguishes displacement from reorganisation, and (c) a set of implications for translator training, procurement, and worker protection.

LITERATURE REVIEW AND RESEARCH QUESTIONS

From Statistical Systems to Large Language Models

Machine translation moved from rule-based and phrase-based systems to neural models within a few years. Castilho et al. (2017) found that NMT outperformed phrase-based systems on fluency and word order, while still struggling with long sentences and some terminology. Toral et al. (2018) showed that post-editing NMT output for a literary text required less effort than post-editing statistical output, although the gains were uneven. LLMs extended this trajectory. Hendy et al. (2023) reported very competitive quality for high-resource languages but weaker performance for low-resource ones, and Jiao et al. (2023) found that ChatGPT performed comparably to commercial services on high-resource European languages but lagged on distant language pairs, although the gap narrowed when GPT-4 was used as the engine. Quality evaluation therefore remains central to professional judgement (Pym, 2013), and the “good enough” threshold differs by text type and risk.

Task Displacement, Complementarity, and the Translation Profession

Labour economists conceptualise automation at the level of tasks rather than jobs. Autor (2015) argued that technology substitutes for routine tasks but complements others, producing polarised demand, and Acemoglu and Restrepo (2019) distinguished the displacement of workers from tasks from the “reinstatement” effect of new tasks. Early evidence on generative AI fits this pattern: Eloundou et al. (2023) estimated that around 80% of the U.S. workforce could have at least 10% of their tasks affected by LLMs, and Noy and Zhang (2023) found that ChatGPT raised the speed and quality of professional writing while narrowing performance gaps between workers.

Translation studies reaches comparable conclusions from a different direction. Pym (2013) argued that, in a machine-translation age, translators’ distinctive skills lie increasingly in revising, selecting, and justifying choices rather than producing every word. Pym and Torres-Simón (2021) reviewed the evidence on automation and concluded that it is changing the profession mainly through workflows and working conditions rather than

abolishing it. Kenny and Doherty (2014) and O'Hagan (2020) make the parallel point for education and practice, namely that technological competence has become part of professional translation competence.

Agency, Resistance, and Working Conditions

The sociology of translation emphasises that technologies are taken up through social negotiation. Olohan (2011) described a "dance of agency" between translators and their tools, and Cadwell et al. (2018) identified both resistance and accommodation among professionals, driven by concerns about quality, status, and rates, but tempered by situations in which MT proved useful. Sakamoto (2019) explained translators' resistance to post-editing through Bourdieu's concept of illusio, the investment in the value of one's craft. Läubli and Orrego-Carmona (2017) documented how professionals publicly interpret machine translation as a threat to colleagues' status. Moorkens (2020) went further, arguing that translation labour is being subjected to a form of "digital Taylorism", in which work is fragmented, monitored, and priced as a commodity. Concern is not confined to workers: Vieira et al. (2021) cautioned that over-reliance on MT in medical and legal settings poses risks that human oversight is meant to contain.

Korean–English as a Distinctive Language Pair

Korean is a subject–object–verb, agglutinative language with frequent omission of subjects and objects and an elaborate system of honorifics (Sohn, 1999), through which speech levels encode relative status and politeness (Brown, 2011). Rendering these features into English requires contextual inference that sentence-level MT has traditionally handled poorly. Korean scholarship now asks the same question for generative AI in literature: Lee (2025) examined how ChatGPT can imitate stylistic variety under different prompts and what this means for the authority of human translators. Experimental work on literary translation in other languages suggests that machine-assisted workflows can constrain creativity and reader engagement relative to human translation (Guerberof-Arenas & Toral, 2022). Together these strands suggest that the KO–EN market should show both rapid automation of routine content and sustained demand for human judgement in culturally dense work.

Research Questions

Guided by the task-based and sociological perspectives above, the study addresses three questions. RQ1: How do the documents describe AI's effect on the composition of KO–EN translation tasks and workflows? RQ2: How do they represent the economic conditions of KO–EN translators, including demand, pricing, and security of work? RQ3: What adaptive strategies and institutional responses do they identify?

METHODOLOGY

Research Design

The study adopts an interpretivist, qualitative design based on document analysis, defined as the systematic review and interpretation of documents to elicit meaning and develop empirical understanding (Bowen, 2009). The approach follows Creswell and Poth's (2018) account of qualitative inquiry as the study of how a phenomenon is represented in its natural context. Document analysis suits a fast-moving and under-

researched topic: the accounts of practitioners, institutions, and journalists are themselves data on how AI is being understood and acted upon in the Korean market, and they can be gathered without burdening a workforce that is already under pressure.

Data Sources and Sampling

Sampling was purposive. English- and Korean-language sources were searched through web search engines and institutional repositories in November 2026. Documents were included if they (a) addressed AI or MT in relation to translation or interpretation work in Korea, or in the global language-services industry; (b) were published between 2016 and 2026; (c) had identifiable authorship and a named publication venue; and (d) reported observations, data, or testimony about work rather than product promotion. Vendor marketing and anonymous forum posts were excluded. The resulting primary corpus (Corpus A) comprised eleven documents (Table 1). A secondary corpus (Corpus B) of peer-reviewed and scholarly works, cited in the literature review, was used to interpret the themes rather than to generate them.

Table 1
Primary Document Corpus (Corpus A, n = 11)

Document	Type	Year	Principal contribution to the analysis
Yoon (n.d.)	News report	n.d.	Human translator versus Papago and Google Translate; arrival of neural MT in Korea
Hwang (2023)	News report	2023	LTI Korea revises translation award rules after AI-use controversy
Park (2023)	News report	2023	Expert views on AI use, disclosure, fee pressure, and the translator's role
Baek et al. (2024)	Technical paper	2024	Cost, latency, and quality of five MT/LLM systems for KO–EN and EN–KO
Jung (2025)	News report	2025	Statistics Korea figures; routine text, post-editing, and expert accountability
Lee (2025)	Scholarly article	2025	Generative AI and the English translation of Korean literature
Nimdzi Insights (2025)	Industry report	2025	Market size, MT adoption, and pricing pressure in language services
MultiLingual (n.d.)	Industry press	n.d.	Korean firms' AI strategies and specialisation of professionals
Jung (2026a)	News report	2026	Association head on post-editing, polarisation, precarity, procurement
Jung (2026b)	Interview	2026	LTI Korea president on human translators and a proposed graduate school
Lee (2026)	News report	2026	Literary translators on AI, ethics, funding, and teaching

Note. MT = machine translation; KO–EN = Korean-to-English; EN–KO = English-to-Korean; n.d. = no date available.

Documents in Corpus A vary in evidentiary weight. News interviews report the views of named association heads, professors, translators, and officials, and the industry report and statistics provide market-level indicators. The technical and scholarly studies supply evidence on system quality and on literary translation. Treating them together allows triangulation across source types, though the corpus should be read as a purposive sample and not as a census of Korean opinion.

Analytic Procedure

Analysis followed the six phases of reflexive thematic analysis (Braun & Clarke, 2006): familiarisation, initial coding, searching for themes, reviewing themes, defining and naming themes, and reporting. Each document was read in full and coded inductively by hand, with codes attached to units of meaning such as a

claim about task change, a quoted experience, or a reported figure. Codes were then clustered into candidate themes, checked against the full data set, and refined. Deductive attention to tasks, pricing, and agency, drawn from the literature, shaped the later review of themes but did not pre-define them. Table 2 presents the final thematic structure.

Trustworthiness and Ethics

Trustworthiness was supported through the criteria proposed by Tracy (2010) and the practices described by Nowell et al. (2017): triangulation across journalism, industry, policy, and scholarly sources; an audit trail of coding decisions; thick description with attributed quotations; reflexive memoing; and a deliberate search for negative cases, such as evidence of stable enrolment in translation programmes. Because the study analyses publicly available documents and involves no human participants, it posed minimal risk. Titles of Korean-language sources were translated by the author, and all statements are attributed to their original speakers and publications.

RESEARCH FINDINGS

Six themes were constructed across the corpus. Table 2 summarises them with representative evidence, and Table 3 collects the quantitative indicators reported in the documents. The themes are presented below in relation to the research questions.

Table 2
Thematic Structure, Representative Evidence, and Research Questions Addressed

Theme	Representative evidence	Main sources	RQ
1. Automation of routine text	"Good enough" AI output for product descriptions; AI captions replace some interpreters	Jung (2025, 2026a); Baek et al. (2024)	RQ1
2. Post-editing as dominant workflow	Growing post-editing share for manuals and technical documents; 69.4% of LSPs plan more MT	Jung (2025, 2026a); Nimdzi Insights (2025)	RQ1, RQ2
3. Polarisation toward high-stakes expertise	Experts hold ground in legal and culturally dense texts; stable graduate-school applications	Jung (2025, 2026a); MultiLingual (n.d.)	RQ1, RQ2
4. Contested authorship in literary translation	Award rules rewritten; LTI Korea president stresses human intervention; ethics and lived experience	Hwang (2023); Park (2023); Lee (2025, 2026); Jung (2026b)	RQ1, RQ3
5. Precarity, pricing, and institutional gaps	No social insurance for freelancers; cheapest-bidder procurement; fee cuts; 15.1% say per-word pricing works	Jung (2026a); Park (2023); Nimdzi Insights (2025); Lee (2026)	RQ2
6. Adaptive role redefinition	Firms build LLMs and evaluation tools; new graduate school proposed; AI taught with verification	MultiLingual (n.d.); Jung (2026b); Lee (2026); Park (2023)	RQ3

Note. LSP = language service provider; LLM = large language model; RQ = research question.

Table 3
Quantitative Indicators Reported in or Derived from the Corpus

Indicator	Value	Source
Registered translation and interpretation firms in Korea, 2020 → 2023	2,429 → 2,805 (+15.5%)	Statistics Korea, as reported by Jung (2025); MultiLingual (n.d.)
Workers in the sector, 2020 → 2023	6,251 → 6,712 (+7.4%)	Statistics Korea, as reported by Jung (2025); MultiLingual (n.d.)
Average workers per firm, 2020 → 2023 (derived)	2.57 → 2.39 (−7.0%)	Author's calculation from the two rows above
Global language-services market, 2024	USD 71.7 billion (+5.6%)	Nimdzi Insights (2025)
LSPs planning to increase MT use	69.4% (up from 63.6%)	Nimdzi Insights (2025)
LSPs saying per-word pricing still works	15.1%	Nimdzi Insights (2025)
Proposed LTI Korea graduate school, initial intake	60 students (30 Korean, 30 international)	Jung (2026b)

Note. Firm and worker counts are not disaggregated by language pair, task, or income. Percentage changes and workers per firm were calculated by the author.

Theme 1: Automation of Routine and High-Volume Text

The documents agree that AI first absorbs standardised, high-volume content. Experts quoted by Jung (2025) said that AI can produce "good enough" translations of product descriptions and similar material, reducing demand for human translators in that segment. Nimdzi Insights (2025) observed that large technology firms now embed translation-like functions in productivity and e-commerce tools, and that machine-translation providers compete with language-service companies for non-critical content. On the system side, Baek et al. (2024) compared GPT-3.5-turbo, GPT-4-turbo, Google, DeepL, and Papago on KO–EN and EN–KO data and found GPT-4-turbo best in quality, Google fastest, and GPT-3.5-turbo cheapest, indicating that the quality–cost trade-off now has several viable options for buyers. Interpreting shows a similar pattern: Jung (2026a) reported that organisers of some international events replaced simultaneous interpreters with automated captions, and that mid-level corporate meetings increasingly use AI interpretation applications.

Theme 2: Post-Editing as the Dominant Workflow

The second theme concerns the form of remaining work. The head of the Korean Association of Translators and Interpreters told Jung (2026a) that the effect is most advanced in post-editing, where AI drafts and humans correct, and that its share is growing for manuals, user guides, and technical documents. Jung (2025) similarly reported rising demand for post-editing in streaming subtitles and AI-assisted customer service for overseas users, and Nimdzi Insights (2025) reported that 69.4% of language-service providers planned to increase MT use, up from 63.6%. The picture is not uniform, however. A translation scholar interviewed by Park (2023) noted that skilled bilingual translators rarely use AI because editing machine output can be less efficient than translating directly, while less fluent translators use it more readily. This negative case suggests that post-editing is expanding through market demand more than through individual preference, a tension consistent with the resistance documented by Cadwell et al. (2018) and Sakamoto (2019).

Theme 3: Polarisation Toward High-Stakes Expertise

Across sources, the market is described as splitting. "Top-class interpreters will survive," the association head said, while providers of basic services face a more polarised market (Jung, 2026a). Experts

told Jung (2025) that AI still trails experienced professionals in legal documents and in content that needs cultural nuance or idiomatic precision, which are among the most lucrative segments, and one interpreting professor argued that humans will remain the final checker because a person can bear legal responsibility for major errors. The industry press describes professionals handing routine work to AI and concentrating on medical documentation, K-pop localisation, and technical manuals, with a professor arguing that legal, diplomatic, and medical texts demand ethical judgement and situational awareness (MultiLingual, n.d.). Consistent with this, officials at two leading translation graduate schools reported stable applications (Jung, 2025).

Theme 4: Contested Authorship in Literary Translation

Literary translation is the arena in which the meaning of human work is most openly contested. In 2023, an award for aspiring translators run by the Literature Translation Institute of Korea (LTI Korea) was placed under review after a winner had used Papago without clear disclosure, and the institute announced that entries must be produced without external aid such as AI (Hwang, 2023; Park, 2023). An ethics expert quoted by Park (2023) argued that the central problem was non-disclosure and the absence of clear rules, not AI use itself. By 2026, the LTI Korea president maintained that, in literature, AI alone cannot meet the standard expected by international publishers without human intervention, and the institute was seeking approval for a degree-granting translation graduate school (Jung, 2026b). Prominent translators likewise argued that translation rests on ethical commitments and lived experience that machines lack, although one educator teaches students to use AI while requiring them to verify its output (Lee, 2026). Scholarly work frames the same tension as a dilemma of fidelity versus the emotional resonance of human imperfection (Lee, 2025).

Theme 5: Precarity, Pricing, and Institutional Gaps

The fifth theme concerns the economic position of workers. Many freelance translators lack social-insurance coverage designed for corporate employees, and the association head warned that public bodies selecting the cheapest bidder for court and parliamentary interpretation would favour AI-based providers, undermining both service quality and the pipeline of skilled interpreters (Jung, 2026a). A scholar cited by Park (2023) described clients who press translators to use AI and then cut fees on the grounds of reduced workload. At the industry level, Nimdzi Insights (2025) reported that only 15.1% of providers believed per-word pricing still works, that falling unit prices were commoditising word-based models, and that pricing pressure was making the field less attractive and thus worsening a shortage of top-tier talent. Literary translators also noted the shift of LTI Korea support toward publisher-led applications and the end of direct-application grants in 2022 (Lee, 2026).

Theme 6: Adaptive Role Redefinition

Despite the pressures, the documents record active adaptation. Experts expect AI to handle first drafts and repetitive work while humans move to higher-value tasks (Jung, 2025), and translators are urged to define their role alongside AI because the market “is never going to completely remove AI from the picture” (Park, 2023). Korean language-service firms are building their own LLMs and evaluation tools, embedding AI

interpretation in workplace software, supplying real-time interpreting to bank branches, and expanding into rarer languages (MultiLingual, n.d.). On the supply side, the proposed LTI Korea graduate school would admit 60 students, half of them international, and is aimed at the shortage of specialist literary translators (Jung, 2026b).

DISCUSSION

The findings answer the three research questions. In response to RQ1, AI is reorganising KO–EN work by automating routine text and shifting remaining effort toward post-editing, quality assurance, and judgement-intensive tasks. This matches the task-based logic of Autor (2015) and Acemoglu and Restrepo (2019): the job category persists while the task mix within it changes, and the "reinstatement" of new tasks, such as post-editing and AI evaluation, is already visible in the documents. In response to RQ2, the economic picture is mixed. Registered firms and workers rose between 2020 and 2023 (Table 3), which cautions against narratives of collapse, yet average workers per firm fell from about 2.57 to 2.39. Because the statistics are not disaggregated by language pair, task, or income, this should be read as suggestive, but it fits accounts of fragmentation into small enterprises and freelancers and of providers facing price pressure (Jung, 2026a; Nimdzi Insights, 2025).

The qualitative evidence also supports the "digital Taylorism" argument (Moorkens, 2020). Fee reductions justified by AI, cheapest-bidder procurement, and the decline of per-word pricing show how technological capability is translated into commercial pressure on workers, independently of whether the technology can match expert quality. Here the distinction between what AI can do and how markets use it is crucial. Theme 3 indicates that the highest-value segments are protected less by technical limits alone than by accountability: legal and diplomatic texts require someone who can be held responsible. This is a plausible mechanism for the premium on top-tier expertise, but it is also a reason to doubt that protection will extend to the large middle of the market.

In response to RQ3, adaptation is occurring at three levels: individual specialisation, firm-level AI integration, and institutional investment in education. The LTI Korea award controversy shows how institutions are still negotiating the boundaries of acceptable AI use, and the ethics expert's call for disclosure rules points to a practical path. The tension between experienced translators who rarely use AI and market demand for post-editing echoes the resistance literature (Cadwell et al., 2018; Sakamoto, 2019), and the literary debates resemble the findings of Guerberof-Arenas and Toral (2022) on creativity. Theme 4 also adds a Korea-specific dimension, because literary translation is entangled with national cultural policy and the global standing of Korean literature.

Three implications follow. First, translator education should integrate post-editing, AI evaluation, and risk assessment alongside traditional skills (Kenny & Doherty, 2014; Pym, 2013). Second, public procurement for legally sensitive interpreting and translation should specify quality and accountability, not only price. Third, freelance protections, such as social insurance for non-employees, deserve policy attention, and professional bodies could develop disclosure guidelines for AI use in awards and contracts.

The study has limitations. It relies on documents rather than direct testimony, so it records how the market is represented, not how it is experienced by individual translators. Three of the eleven documents share a single journalist, and sources skew toward Seoul-based institutions and toward literature and interpreting. The statistics are not disaggregated for KO–EN, no income series was available, and the single-coder design limits intersubjective checking. Future research should add interviews with KO–EN freelancers, agency managers, and clients; analyse job-posting and rate data; and compare automation effects across text types.

CONCLUSION

This study examined how AI is reshaping the Korean-to-English translation job market through a qualitative analysis of Korea-focused and industry documents. It found that AI is automating routine text, making post-editing the dominant mode of remaining work, polarising the market toward high-stakes expertise, unsettling literary authorship, and intensifying pricing and welfare pressures, while prompting adaptation by individuals, firms, and institutions. Overall, AI appears to be displacing tasks more than occupations, but the burdens of this transition fall unevenly, most heavily on mid-tier and freelance workers. Interviews and market data are needed to test these interpretations, and policy attention to disclosure, procurement, and worker protection would help ensure that productivity gains from AI do not come at the expense of the human expertise that high-stakes translation still depends on.

REFERENCES

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Baek, S., Lee, S., & Seok, J. (2024). Strategic insights in Korean-English translation: Cost, latency, and quality assessed through large language model. In *2024 15th International Conference on Ubiquitous and Future Networks (ICUFN)* (pp. 551–553). IEEE. https://doi.org/10.1109/ICUFN61752.2024.10625181

Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal, 9*(2), 27–40. https://doi.org/10.3316/QRJ0902027

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brown, L. (2011). *Korean honorifics and politeness in second language learning*. John Benjamins.

Cadwell, P., O'Brien, S., & Teixeira, C. S. C. (2018). Resistance and accommodation: Factors for the (non-) adoption of machine translation among professional translators. *Perspectives, 26*(3), 301–321. https://doi.org/10.1080/0907676X.2017.1337210

Castilho, S., Moorkens, J., Gaspari, F., Calixto, I., Tinsley, J., & Way, A. (2017). Is neural machine translation the new state of the art? *The Prague Bulletin of Mathematical Linguistics, 108*, 109–120. https://doi.org/10.1515/pralin-2017-0013

Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.

Cronin, M. (2013). *Translation in the digital age*. Routledge.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An early look at the labor market impact potential of large language models*. arXiv. https://doi.org/10.48550/arXiv.2303.10130

Guerberof-Arenas, A., & Toral, A. (2022). Creativity in translation: Machine translation as a constraint for literary texts. *Translation Spaces, 11*(2), 184–212. https://doi.org/10.1075/ts.21025.gue

Hendy, A., Abdelrehim, M., Sharaf, A., Raunak, V., Gabr, M., Matsushita, H., Kim, Y. J., Afify, M., & Awadalla, H. H. (2023). *How good are GPT models at machine translation? A comprehensive evaluation*. arXiv. https://doi.org/10.48550/arXiv.2302.09210

Hwang, D. (2023, February 9). LTI Korea to set new rules for translation award after AI translation sparks controversy. *The Korea Herald*. https://v.daum.net/v/2KLgiEo5xZ

Jiao, W., Wang, W., Huang, J., Wang, X., Shi, S., & Tu, Z. (2023). *Is ChatGPT a good translator? Yes with GPT-4 as the engine*. arXiv. https://doi.org/10.48550/arXiv.2301.08745

Jung, M. (2025, August 11). Will AI replace human translators? *The Korea Times*. https://www.koreatimes.co.kr/southkorea/society/20250811/will-ai-replace-human-translators

Jung, M. (2026a, April 24). Declining income, no consent: AI eats into Korea's creative, language workforce. *The Korea Times*. https://www.koreatimes.co.kr/southkorea/society/20260424/declining-income-no-consent-ai-eats-into-koreas-creative-language-workforce

Jung, M. (2026b, June 20). [Interview] LTI Korea chief bets on human translators despite rapid AI development. *The Korea Times*. https://www.koreatimes.co.kr/lifestyle/books/20260620/lti-korea-chief-bets-on-human-translators-despite-rapid-ai-development

Kenny, D., & Doherty, S. (2014). Statistical machine translation in the translation curriculum: Overcoming obstacles and empowering translators. *The Interpreter and Translator Trainer, 8*(2), 276–294. https://doi.org/10.1080/1750399X.2014.936112

Läubli, S., & Orrego-Carmona, D. (2017). When Google Translate is better than some human colleagues, those people are no longer colleagues. In *Proceedings of Translating and the Computer 39*. AsLing.

Lee, H.-J. (2025). 생성형 인공지능(AI)의 한국문학 영어번역의 딜레마와 가능성 [Generative artificial intelligence's English translation of Korean literature and its dilemmatic possibility]. *외국문학연구, 100*, 59–87. https://doi.org/10.22344/fls.2025.100.59

Lee, H.-R. (2026, October 8). Korean literature needs translator autonomy to reach global readers. *The Korea Times*. https://www.koreatimes.co.kr/lifestyle/books/20261008/korean-literature-needs-translator-autonomy-to-reach-global-readers

Moorkens, J. (2020). "A tiny cog in a large machine": Digital Taylorism in the translation industry. *Translation Spaces, 9*(1), 12–34.

MultiLingual. (n.d.). South Korea: Boom in translation and interpretation in the AI era. *MultiLingual*. https://multilingual.com/?p=225245

Nimdzi Insights. (2025). *The 2025 Nimdzi 100*. https://www.nimdzi.com/nimdzi-100-2025

Nowell, L. S., Norris, J. M., White, D. E., & Moules, N. J. (2017). Thematic analysis: Striving to meet the trustworthiness criteria. *International Journal of Qualitative Methods, 16*(1), Article 1609406917733847. https://doi.org/10.1177/1609406917733847

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

O'Hagan, M. (Ed.). (2020). *The Routledge handbook of translation and technology*. Routledge.

Olohan, M. (2011). Translators and translation technology: The dance of agency. *Translation Studies, 4*(3), 342–357. https://doi.org/10.1080/14781700.2011.589656

Park, H. (2023, February 10). How will AI affect translators of the future? *The Korea Times*. https://www.koreatimes.co.kr/lifestyle/trends/20230210/how-will-ai-affect-translators-of-the-future

Pym, A. (2013). Translation skill-sets in a machine-translation age. *Meta, 58*(3), 487–503. https://doi.org/10.7202/1025047ar

Pym, A., & Torres-Simón, E. (2021). Is automation changing the translation profession? *International Journal of the Sociology of Language, 2021*(270), 39–57. https://doi.org/10.1515/ijsl-2020-0015

Sakamoto, A. (2019). Why do many translators resist post-editing? A sociological analysis using Bourdieu's concept of illusio. *The Journal of Specialised Translation, 31*, 201–216.

Sohn, H.-M. (1999). *The Korean language*. Cambridge University Press.

Toral, A., Wieling, M., & Way, A. (2018). Post-editing effort of a novel with statistical and neural machine translation. *Frontiers in Digital Humanities, 5*, Article 9. https://doi.org/10.3389/fdigh.2018.00009

Tracy, S. J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. *Qualitative Inquiry, 16*(10), 837–851. https://doi.org/10.1177/1077800410383121

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems 30* (pp. 5998–6008). Curran Associates.

Vieira, L. N., O'Hagan, M., & O'Sullivan, C. (2021). Understanding the societal impacts of machine translation: A critical review of the literature on medical and legal use cases. *Information, Communication & Society, 24*(11), 1515–1532. https://doi.org/10.1080/1369118X.2020.1776370

Yoon, S. (n.d.). AI programs take on human translators in South Korea. *South China Morning Post*. https://www.scmp.com/news/asia/east-asia/article/2071036/ai-programmes-take-human-translators-south-korea