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# AI and the Next Era of Translation: A Critical Inquiry on Advantages, Risks, and Future Venues

*[1]Asghar Moulavinafchi**, *[2]Sayyede Maryam Hosseini*, *[3]Reyhane Sadat Shadpour*, & *[4]Yasir Hazim Qasim Qasim*

## ABSTRACT

With the widespread adoption of artificial intelligence (AI), translation practices have been reconfigured in ways that reflect broader shifts in digital labor and knowledge economies. This study critically explores the benefits and challenges of AI-assisted translation from the perspective of professional translators. Using a qualitative approach, semi-structured interviews were conducted with 20 translators, each with over three years of experience, recruited from diverse linguistic, cultural, and specialization backgrounds. Thematic analysis of the Zoom interviews revealed that AI offers perceived efficiencies, such as increased productivity, cost reduction, and consistent terminology, especially in technical or repetitive tasks. These benefits are embedded within asymmetrical power relations shaped by platform capitalism and automation ideologies. However, significant challenges persist, including AI's difficulty with cultural nuance, over-reliance on automation, post-editing fatigue, and ethical concerns like data privacy and job security. Translators stressed that AI should be used as a supportive tool, not a replacement for human expertise—particularly where creativity and cultural sensitivity are crucial. The study highlights the need for targeted training, clear ethical guidelines, and hybrid approaches that combine the strengths of both AI and human translators.

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1 **Corresponding Author**: Assistant Professor, Department of English Language and Literature, Faculty of Literature and Humanities, Hakim Sabzevari University, Sabzevar, Iran;
Email: a.moulavi@hsu.ac.ir ; ORCID: https://orcid.org/0000-0002-7495-2333
2 Assistant Professor, English Language Department, Faculty of Humanities, University of Zanjan, Zanjan, Iran;
Email: Mshosseini891@gmail.com; ORCID: https://orcid.org/0000-0002-3476-1508
3 Ph.D. Candidate, Adjunct Lecturer, English Language and Literature Department, Faculty of Literature and Humanities, Hakim Sabzevari University, Sabzevar, Iran;
Email: r.s.shadpour@gmail.com ; ORCID: https://orcid.org/0009-0006-2428-0563
4 Ph.D. Candidate of TEFL, English Language and Literature Department, Faculty of Literature and Humanities, Hakim Sabzevari University, Sabzevar, Iran and Assistant teacher, Iraqi Ministry of Education/Basra Education Directorate, Basra, Iraq;
Email: yasir.hazim.qasim@gmail.com; ORCID: https://orcid.org/0009-0009-1299-7024
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## 1. Introduction

Across diplomacy, commerce, migration, and online culture, translation has shifted from a back-office craft to an always-on infrastructure layer—and AI is now the main force reshaping how that infrastructure is built, taught, and trusted. Contemporary translation ecosystems increasingly rely on neural machine translation (NMT), statistical machine translation (SMT), and computer-assisted translation (CAT) workflows that promise faster throughput, lower cost, and broader access to multilingual information (Amini et al., 2024; Chen et al., 2022; Cope et al., 2021). In translation education, these tools are no longer peripheral: evidence from classroom-oriented implementations suggests measurable gains in speed and learning support, with AI-driven systems reporting higher translation performance and favorable instructor evaluations when integrated into training and feedback loops (Klimova et al., 2023; Lee, 2020; Yuxiu, 2024). For example, an AI translation teaching system combining NMT and SMT reported markedly higher translation accuracy than traditional MT and high teacher satisfaction ratings, positioning AI not just as a productivity aid, but as a pedagogical instrument that can reshape assessment, practice frequency, and learner autonomy (Yuxiu, 2024). At the same time, the field is far from settled: translation quality remains uneven across domains, language pairs, and pragmatic contexts, and "better BLEU" does not necessarily mean better meaning, cultural fit, or ethical acceptability in high-stakes settings (Amini et al., 2024; Pan et al., 2022). This is why the present study frames "the next era" of translation as more than a technical upgrade: it calls for a qualitative, critically oriented inquiry into where AI genuinely improves translation work, where it introduces new fragilities (bias, privacy leakage, deskilling, false confidence), and what future pathways—curricular, professional, and technological—can keep human judgment and accountability in the loop (Liu & Afzaal, 2021; Soysal, 2023; Weisz et al., 2021).

A critical starting point is definitional and epistemic: if AI is, as Garrison describes, "computers which perform cognitive tasks…particularly learning and problem-solving" (Garrison, 2007, p. 62), then translation becomes a prime test case because it demands linguistic, cultural, and situational cognition—not merely symbol substitution. Machine learning itself is often framed as "software that is able to recognize patterns, make predictions, and apply…patterns" beyond initial design (Wilks, 1972, p. 2), which aligns with why NMT has advanced so quickly on large corpora and attention-based sequence models (Mnih et al., 2015;

Sutskever et al., 2014). Yet the classic critique still bites: “Expert human translators use their background knowledge mostly subconsciously…[to] resolve syntactical and semantic ambiguities,” a capability machines may mishandle or mechanize poorly (Wilks, 1973, p. 101). Even strong AI proponents concede the core requirement that “high-quality machine translation is possible only when the text…has been understood” by the mechanism (Minsky, 1975), and “understanding” here includes pragmatics, implicature, register, and culturally loaded meaning—precisely where AI systems still show brittle behavior, stereotype amplification, or context loss (Amini et al., 2024; Soysal, 2023). The educational parallel is equally blunt: “strengthening the connection between AI developers and experts in the learning sciences” is a prerequisite, otherwise tools can scale bad pedagogy as efficiently as good pedagogy (Lynch & Park, 2017). These tensions make the case for qualitative methods: interviews and critical thematic analysis can surface where users experience advantage (speed, access, feedback immediacy) versus risk (automation bias, privacy exposure, labor displacement, ethical drift), and how hybrid models—human post-editing, policy guardrails, transparent evaluation, and curriculum reform—can produce translations that are not only fluent, but socially responsible (Jobin et al., 2019; Morley et al., 2021; Morley et al., 2023; Weisz et al., 2021). In short, the “next era” will not be defined by whether AI can translate, but by how institutions choose to govern, teach, and professionalize human–AI translation so that capability gains do not outpace accountability.

## 2. Literature Review

### *2.1. AI as a General-Purpose Infrastructure Reshaping Translation Work*

AI has moved from a specialized research agenda to a general-purpose infrastructure that now shapes how language work is produced, evaluated, priced, and governed. In translation, this shift has intensified long-standing debates about automation, quality, and professional identity, but it has also introduced qualitatively new dynamics through large language models (LLMs) and “generative AI translation” workflows in which translators can steer outputs via prompts and iterative revision. Popular narratives often frame AI as either a technological leap or a translator’s nightmare, a polarity that has become especially salient in university contexts where instructors must both interpret the technology and prepare students for its realities (Amini et al., 2024; Bouguesmia, 2020).

This "next era" therefore requires a critical inquiry that does not merely compare machine output to human output, but examines advantages, risks, and pathways that could plausibly sustain quality, ethics, and professional relevance. Recent empirical work comparing ChatGPT-generated translation and human translation in scientific texts suggests a more nuanced picture: GenAI can show strengths in terminological consistency and certain lexical/syntactic patterns, while human translators exhibit advantages in restructuring complex sentences and improving comprehensibility—an interactional framing that points toward hybrid future models rather than simple substitution (Fu & Liu, 2024; Moorkens, 2018). At the same time, market forecasts and industry claims about rapid displacement amplify the urgency of studying practitioner perceptions, willingness to contribute to development, and conditions for responsible adoption—particularly among educators who influence curricular and ethical norms (Marr, 2018; Massey & Ehrensberger-Dow, 2017).

The present study's qualitative orientation aligns with this landscape: adoption is not determined by capability alone; it is shaped by trust, perceived risk, institutional constraints, and epistemic beliefs about what "good translation" is and who is accountable for it (Liu et al., 2022; Newmark, 1981).

### *2.2. Defining AI: Conceptual Contests and Practical Implications for Translation*

Defining AI is itself contested because "intelligence" is not a single measurable trait but an umbrella for learning, reasoning, adaptation, and goal-directed action. Common definitional cores portray AI as the capability of digital systems to perform tasks associated with human intelligence, especially learning from experience and reasoning under uncertainty (Copeland, 2020; McCarthy, 2007; Rouse, 2020). Philosophical accounts emphasize that AI is both an engineering project (building systems that behave intelligently) and a scientific project (understanding the phenomenon of intelligence), which is why definitions tend to oscillate between functional performance and cognitive analogy (Bringsjord & Govindarajulu, 2018; Kiger, 2019).

In operational terms for translation studies, AI typically enters through natural language processing (NLP), machine learning (ML), and deep learning architectures trained on large corpora to model language patterns and generate outputs that appear fluent and contextually appropriate (Das, 2018; LeCun et al., 2015). This grounding matters because many translations controversies hinge on a mismatch between what AI optimizes (probabilistic pattern completion, often at sentence level) and what translation as a social practice demands (situated meaning, accountability, pragmatic intent, and cultural form). The weak/strong AI distinction is often invoked here: “narrow” AI can be highly competent in bounded tasks but fails when meaning depends on social inference or novel world knowledge, while “strong” AI remains aspirational and raises ethical anxieties about autonomy and agency (Hintze, 2016; Rouse, 2020). For translation, this implies that today’s systems—however impressive—operate as specialized tools that may excel in high-regularity domains yet remain brittle in figurative language, interpersonal stance, or culturally dense text types (Alowedi & Al-Ahdal, 2023; Das, 2018).

### *2.3. AI Typologies, Social Cognition Gaps, and Equity Across Languages*

Typologies of AI also clarify why translation technology evolves unevenly across tasks. Reactive systems, limited-memory systems, “theory of mind” systems, and self-aware systems represent increasing degrees of internal modeling and social inference (Hintze, 2016). Translation engines historically resembled reactive systems: given an input, apply rules, templates, or statistical mappings. Modern neural systems add limited-memory characteristics via attention mechanisms and context windows, yet they still struggle to represent speaker intention, irony, and socio-pragmatic nuance that “theory of mind” accounts would regard as core to human communication (Das, 2018; Hintze, 2016). This gap becomes visible in examples where machine outputs are grammatically plausible but pragmatically wrong—errors that are not simply “bugs” but symptoms of missing social cognition and contextual grounding.

Further, AI design is not neutral: system behavior reflects data composition, annotation choices, and developer assumptions, producing systemic bias and uneven performance across languages and varieties (Das, 2018; Liu et al., 2022). These concerns are magnified in translation because language differences encode power relations: high-resource languages benefit from abundant data, while low-resource languages face sparse corpora, weaker generalization, and greater risk of meaning distortion (Das, 2018; Hong, 2018). Consequently, adoption decisions must be evaluated not only for accuracy but for equity: which communities receive reliable translation and which become “second-class” users of language technology.

### *2.4. From Early Machine Translation to Neural and Generative Paradigms*

The historical trajectory from early machine translation to neural and generative paradigms explains both the optimism and the backlash. Conceptual roots often trace to questions like whether machines can "think" in a linguistically indistinguishable way, a topic associated with the Turing Test and earlier philosophical concerns about machine language competence (Pestov, 2018; Titz, 2018). Early mechanical translation efforts—particularly Troyanskii's work—show that the desire to automate translation predates modern computing and was constrained by physical media and limited linguistic modeling (Hutchins, 2004; Hutchins & Lovtskii, 2000). The Georgetown–IBM demonstration in the 1950s helped legitimize MT politically and commercially, but subsequent disillusionment (including the well-known funding contraction in the U.S.) illustrates a persistent pattern: public expectations often exceed what systems can reliably deliver outside curated test conditions (Pestov, 2018; Titz, 2018).

Technically, the field moved through example-based machine translation (leveraging parallel examples), statistical machine translation (probabilistic phrase mappings), and neural machine translation (encoder–decoder architectures that learn representations and generate sequences) (Cho et al., 2014; Das, 2018; Zong, 2018). Seminal neural work established sequence-to-sequence learning and attention-based alignment as foundations for end-to-end translation, enabling major platforms to deploy NMT at global scale (Bahdanau et al., 2015; Sutskever et al., 2014; Wu et al., 2016). Multilingual and "zero-shot" extensions further reframed translation as a shared representation problem, reducing reliance on pivot languages and improving scalability—though not eliminating quality asymmetries (Johnson et al., 2017; Toral & Sánchez-Cartagena, 2017).

This arc matters for qualitative inquiry because professional anxiety is not merely fear of automation; it is a repeated social pattern following each "breakthrough," with jobs, training, and ethical expectations reorganized around new tool capabilities and new failure modes (Bouguesmia, 2020; Marr, 2018).

### *2.5. Persistent Limits of NMT and the Continuing Centrality of Human Expertise*

Despite notable improvements, research consistently identifies limits that keep human expertise central, especially when translation quality is defined as adequacy, pragmatic fit, and cultural intelligibility rather than surface fluency. NMT remains vulnerable to contextualization failures, figurative language errors, and sociocultural mismatches, which appear prominently in analyses of idioms, sarcasm, irony, humor, and culturally anchored expressions (Alowedi & Al-Ahdal, 2023; Das, 2018). Known system behaviors include under-translation and over-translation, inconsistent lexical choices, and errors that lack transparent patterns for users—a key reason trust remains fragile in high-stakes settings (Das, 2018; Tu et al., 2016).

Proposed technical remedies (e.g., coverage models, reconstruction-based frameworks, minimum risk training, and decoding objectives that promote diversity and adequacy) demonstrate that "quality" is partly an optimization choice, not an automatic byproduct of scale (Li & Jurafsky, 2016; Shen et al., 2016; Tu et al., 2017). However, technical fixes do not fully resolve discourse-level issues: studies show weaker cohesion and coherence in machine outputs compared with human translation, and corpus-based work suggests "translationese" signatures and reduced linguistic richness can persist even when sentence-level metrics improve (Frankenberg-Garcia, 2022; Jiang & Niu, 2022; Vanmassenhove et al., 2019). These findings complicate simplistic claims that MT is "at parity" with humans, because parity depends on genre, language pair, evaluation criteria, and user purpose (Ahrenberg, 2017; Muftah, 2022). In practice, then, the decisive question is not whether AI can translate, but under what constraints it translates reliably enough, and who bears accountability when it fails.

### *2.6. Evaluation: Metrics, Human Judgments, and Accountability in High-Stakes Contexts*

Evaluation research reinforces this caution. Automatic metrics such as BLEU enabled fast benchmarking and were instrumental in system development, yet they are proxy measures that can reward n-gram overlap without capturing pragmatic adequacy, discourse coherence, or stylistic intent (Hovy, 1999; Papineni et al., 2002). Human-centered frameworks emphasize adequacy, fluency, fidelity, and purpose, and they show that evaluation must be sensitive to task and domain—particularly in contexts like healthcare, diplomacy, and law where errors carry material consequences (Reeder, 2001; White & O'Connell, 1994).

Even when platform leaders cite metric gains as evidence that "human quality is near," critical responses argue that such claims often rest on narrow test sets and underrepresent failures in creativity, literary voice, or cross-cultural pragmatics (Das, 2018; Hofstadter, 2018). The consequence for translation studies is methodological: a qualitative study that asks educators about perceived advantages and risks is not a "soft" alternative to benchmarking; it targets an adjacent reality—how humans interpret and govern technology under uncertainty. Instructors and translators form judgments about trustworthiness, acceptable use, and ethical boundaries based on observed errors, institutional norms, and lived accountability, not just BLEU deltas (Bouguesmia, 2020; Liu et al., 2022). Therefore, examining awareness, attitudes, and willingness to engage in AI development is a legitimate empirical route to understanding how the next era will be negotiated in practice.

### *2.7. Generative AI and Prompt-Based Translation Workflows*

Generative AI has intensified these issues because it alters both the interface and the labor model of translation. Unlike classical NMT products that present a translation as a static output, LLM-based systems can respond conversationally, accept constraints, and revise outputs iteratively—which shifts translator work toward steering, auditing, and post-editing via prompt-based interaction (Jiao et al., 2023; Oppenlaender et al., 2023). Early evidence indicates that GPT-style systems can be strong at certain translation tasks, yet their performance varies with prompting, text type, and language direction, and they can still hallucinate, oversimplify, or produce subtly unfaithful discourse relations (Hendy et al., 2023; Wang et al., 2023).

In scientific translation specifically, the comparative study of GenAIT and human translation suggests complementarity: GenAI can show higher accuracy in some terminology and maintain formal structures, while human translators more actively restructure long sentences and improve readability by segmenting and re-encoding meaning in target-language-appropriate ways (Fu & Liu, 2024). This complements broader findings in translation studies about explicitation and simplification patterns and the ways different systems exhibit translation universals or translationese traits (Baker, 1993; Krüger, 2020; Lapshinova-Koltunski, 2015). Importantly, such complementarity implies that the future pathway is not a binary choice between humans and machines, but a design problem: how to allocate tasks, controls, and responsibility between GenAI outputs and human judgment. For translator education, the practical implication is that competence may increasingly include tool orchestration, error diagnosis, and prompt literacy—skills that are teachable but also ethically loaded because they determine what gets delegated and what gets verified (Amini et al., 2024; Oppenlaender et al., 2023).

### 2.8. The "Next Era" as a Socio-Technical Transition: Benefits, Risks, and Governance

Finally, the "next era" must be treated as a socio-technical transition with clear benefits and real risks. On the advantage side, AI-enabled translation can increase speed, lower cost, expand access to information, and support multilingual communication in near-real time—especially in high-volume, formulaic, or terminology-heavy settings where consistency and throughput matter (Amini et al., 2024; Hong, 2018). For languages with ample data, NMT and GenAI can offer strong baseline quality that can be refined through post-editing, and some industry voices predict large market shifts toward automation and FAUT-like utility in coming decades (Marr, 2018; Massey & Ehrensberger-Dow, 2017).

On the risk side, evidence highlights persistent fragilities: cultural and pragmatic misrenderings, bias embedded in data patterns, weaker performance for less-resourced languages, and the absence of fully reliable self-evaluation mechanisms in real-world unconstrained deployment (Das, 2018; Vanmassenhove et al., 2019). These risks translate into governance questions that qualitative inquiry is well suited to surface: What do educators consider acceptable use? Where do they locate accountability? How do they balance productivity gains with pedagogical aims and professional ethics? Bouguesmia's focus on translation teachers' awareness, emotional orientation, and willingness to contribute to AI development foregrounds precisely these levers of adoption and resistance (Bouguesmia, 2020). In parallel, research on instructor and learner perceptions shows that sustainability of MT use in education depends on trust, transparency, and alignment with learning outcomes rather than mere availability (Liu et al., 2022).

Therefore, future pathways that are credible will likely emphasize human-in-the-loop workflows, domain-sensitive evaluation, bias-aware data practices, and curriculum reforms that teach both linguistic competence and critical technological literacy. The central hypothesis emerging from the literature is not that AI will eliminate translation, but that it will reorganize translation: shifting value toward those who can reliably control quality, manage risk, and justify decisions in contexts where language is inseparable from power, responsibility, and consequence.

Although existing research has substantially advanced understanding of machine translation and, more recently, LLM-based "generative AI translation," it remains disproportionately focused on output comparisons and technical quality indicators rather than the broader adoption conditions that determine real-world use. In particular, many studies document strengths and weaknesses by text type or metric, but provide limited integrated evidence on how advantage claims, risk perceptions, and governance constraints interact in practice, especially in educational settings where decisions shape professional norms and student competencies.

A second gap is the limited attention to translation educators as pivotal decision-makers in this transition. While practitioner perceptions are discussed in parts of the literature, fewer studies treat educators as curriculum architects and ethical gatekeepers whose interpretations directly influence acceptable use policies, assessment practices, and what "competence" means in the AI era. This matters because the sustainability and legitimacy of AI adoption in training contexts depend on institutional trust, accountability expectations, and alignment with learning outcomes—not only on system capability.

A third gap concerns the lack of a unified, pathway-oriented framing that moves beyond a replacement-versus-assistance narrative. Even when complementarity between humans and GenAI is acknowledged, fewer studies offer empirically grounded accounts of plausible future pathways specifying how translation workflows, quality assurance, responsibility allocation, and curriculum content should be reorganized under prompt-based, iterative interaction. As a result, the field still needs holistic qualitative evidence that captures perceived advantages, perceived risks, and credible future integration pathways within a single analytic frame. Therefore, the current study seeks to find an answer to the following research question:

RQ: How do translation educators perceive the advantages, risks, and future pathways of generative AI in translation and translator education?

## 3. Methodology

### *3.1. Research Design*

This study adopts a qualitative research design to examine how professional translators experience and interpret the increasing use of AI tools in translation work. Because the aim is to understand perceptions, meanings, and decision-making in context rather than to test predefined variables, a phenomenological orientation is used to capture participants' lived experiences and the ways they make sense of AI's influence on their workflows, professional identity, and quality judgments (Creswell & Poth, 2018; van Manen, 2016). Trustworthiness is strengthened through systematic documentation of decisions during the study, the inclusion of multiple participants with varied backgrounds, and member checking in which preliminary interpretations are shared with participants to confirm accuracy and resonance (Lincoln & Guba, 1985). Ethical safeguards are treated as integral to the design: participants receive clear information about the study purpose, procedures, potential risks, and their right to withdraw without penalty prior to providing consent. Anonymity and confidentiality are protected by de-identifying all records and reporting findings in aggregate. Formal approval from the relevant institutional review board was obtained before any recruitment or data collection activities began.

### *3.2. Participants*

Participants were professional translators with a minimum of three years of translation experience, a criterion intended to ensure that interviewees had sustained exposure to industry expectations and could reflect meaningfully on changes introduced by AI tools. A purposive sampling strategy was used to recruit individuals likely to provide rich, information-dense accounts directly relevant to the research focus (Patton, 2015). Recruitment proceeded in two stages. First, an invitation was circulated through professional and online translator communities, including channels associated with the American Translators Association, ProZ.com, and translator groups on Telegram, to reach a broad range of practitioners. Second, interested individuals completed an online screening form (Appendix A) that confirmed eligibility and collected background information related to experience level, familiarity with AI, and availability for interviews. Based on these criteria, 20 translators were selected to reflect variability in demographics, professional experience, and self-reported AI familiarity, thereby supporting analytical breadth while maintaining the qualitative emphasis on depth.

### *3.3. Instruments*

Data were generated through a multi-instrument qualitative package designed to capture both participants' stated perceptions and their enacted decision-making while working with AI. First, an eligibility screener and background questionnaire were used to document participants' professional profile, language pairs, and AI-use patterns, and to confirm inclusion criteria. Second, participants completed a short, screen-recorded AI-assisted translation task using their typical workflow and preferred tools. This task was intended to surface concrete moments of tool reliance, verification, and revision in a realistic setting rather than relying only on retrospective self-report. Third, a semi-structured stimulated-recall interview followed immediately, during which the researcher referenced salient moments from the task (e.g., prompting choices, edits, or verification steps) to elicit participants' reasoning, perceived advantages, perceived risks, and views on credible future pathways for the profession. The combined instruments support triangulation across self-report, observed practice, and reflective explanation.

### *3.4. Data Collection*

Recruitment began with a targeted invitation distributed through professional translator networks and online communities. Interested individuals completed the screening and background questionnaire to verify eligibility and to capture baseline information about their experience and familiarity with AI-assisted translation. Eligible participants were then scheduled for a single remote session. At the start of the session, the researcher reviewed the study purpose, data protections, and participants' rights, and obtained informed consent for audio and screen recording.

The session proceeded in two consecutive phases. In phase one, participants completed a brief translation task while sharing their screen on Zoom (or an equivalent platform). Participants used their usual resources (e.g., CAT tools, dictionaries, termbases, AI systems), but were instructed not to use any confidential client materials; the researcher provided short, non-confidential texts to standardize the task and reduce privacy risk. Where feasible, participants captured prompts and AI outputs in a simple log template, and the screen recording served as the primary behavioral record. In phase two, the researcher conducted a stimulated-recall semi-structured interview anchored in the task, encouraging participants to explain why they accepted, rejected, or revised AI suggestions and how they evaluated quality, accountability, and risk in practice. Recordings were transcribed verbatim, anonymized through removal of identifying information, and stored on password-protected devices. To enhance credibility, the researcher conducted member checking by sharing a brief summary of interpreted themes with participants for confirmation or correction.

### *3.5. Data Analysis*

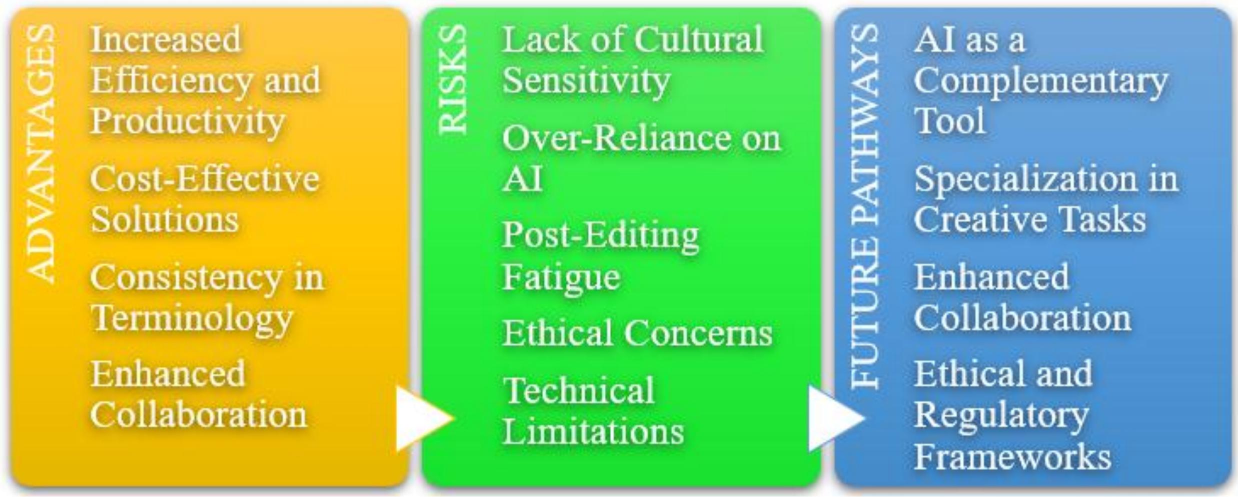
Interview data were analyzed using thematic analysis following Braun and Clarke's (2006) framework because it offers a rigorous yet flexible approach to identifying patterned meanings across a qualitative dataset. Analysis began with familiarization, during which the researcher read and re-read transcripts to develop an overall sense of participants' accounts and to note preliminary analytic observations. The next stage involved initial coding, where meaning-bearing segments of text were systematically labeled to capture relevant ideas related to translators' experiences with AI, perceived benefits, concerns, and anticipated developments. Codes were then examined and clustered into candidate themes that represented broader recurring patterns across participants. These themes were iteratively reviewed against the dataset to ensure internal coherence within themes and clear distinction between themes, after which they were refined and defined with careful attention to scope and meaning. Finally, the themes were organized into an interpretive narrative that addressed the study focus and represented both commonalities and important variations in participants' perspectives. To strengthen dependability, the researcher consulted a colleague with qualitative research expertise to review and discuss coding decisions and theme interpretation, supporting a more disciplined analytic process and reducing the likelihood of idiosyncratic conclusions (Braun & Clarke, 2006).

## 4. Findings

Using an inductive thematic analysis of the interview dataset, the analysis converged on 13 salient themes that organize participants' accounts of AI in translation across three macro-domains: (i) Advantages (4 themes), (ii) Risks (5 themes), and (iii) Future Pathways (4 themes) (see Figure 3). Rather than describing AI as a single "technology," participants positioned it as a workflow infrastructure—a set of tools that re-shapes pacing, decision-making, accountability, and even how value is negotiated between translators and clients. In the findings below, themes are presented as interpretive patterns: each theme captures not only what participants said, but how they framed the role of AI—sometimes as an accelerator, sometimes as a liability, and often as both simultaneously. The discussion is supported by illustrative interview excerpts (paraphrased in form, but retaining the original meaning), with some quotes intentionally short and others extended to reflect the range of participants' emphasis and narrative depth.

**Figure 1**

*Identified Themes on the Advantages, Risks, and Future Pathways of AI in Translation*




In qualitative thematic analysis, frequency tables are best used as descriptive transparency tools rather than as "proof" of importance. Here, frequency (n) indicates the minimum number of participants represented in the illustrative excerpts for each theme (i.e., the number of distinct participant IDs quoted under that theme). Percentages simply convert that count into a share of the sample (n/20). That said, two cautions matter:

1. Frequency ≠ significance. A theme mentioned by fewer participants can still be crucial if it is high-impact (e.g., ethical risk in legal/medical translation) or conceptually central.

2. Counts can overlap. The same participant may contribute to multiple themes, so the sum across themes will exceed 20. This is normal in thematic reporting because themes are not mutually exclusive.

**Table 1**

*Frequency and Percentage of Each Theme/Sub-theme (N = 20)*

| Main Theme | Sub-theme (Theme) | Quoted Participants (n) | % of participants |
|---|---|---|---|
| Advantages of AI in Translation | Theme 1: Increased Efficiency and Productivity | 3 | 15.0% |
| | Theme 2: Cost-Effective Solutions | 2 | 10.0% |
| | Theme 3: Consistency in Terminology | 2 | 10.0% |
| | Theme 4: Enhanced Collaboration | 2 | 10.0% |
| Risks of AI in Translation | Theme 1: Lack of Cultural Sensitivity | 3 | 15.0% |
| | Theme 2: Over-Reliance on AI | 2 | 10.0% |
| | Theme 3: Post-Editing Fatigue | 1 | 5.0% |
| | Theme 4: Ethical Concerns | 2 | 10.0% |
| | Theme 5: Technical Limitations | 1 | 5.0% |
| Future Pathways of AI in Translation | Theme 1: AI as a Complementary Tool | 1 | 5.0% |
| | Theme 2: Specialization in Creative Tasks | 2 | 10.0% |
| | Theme 3: Enhanced Collaboration | 2 | 10.0% |
| | Theme 4: Ethical and Regulatory Frameworks | 1 | 5.0% |

Overall, the frequency pattern suggests that participants most visibly foregrounded workflow-related value (e.g., efficiency/productivity) and human-centered limitations (e.g., cultural sensitivity), each represented by 15% of the sample in the quoted evidence. A second tier of themes—cost effectiveness, terminology consistency, enhanced collaboration, over-reliance, and ethical concerns—appears with 10% representation each, indicating a broad but less concentrated emphasis across practical and professional dimensions of AI-mediated translation. Finally, a smaller set of themes—post-editing fatigue, technical limitations, AI as a complementary tool, and ethical/regulatory frameworks—is represented at 5% each within the quoted excerpt set; in a qualitative frame, these should not be treated as marginal, especially because such themes often reflect high-stakes risks (privacy, liability, cognitive load) or structural solutions (governance) that may emerge from fewer but more detailed narratives.

### *4.1. Advantages of AI in Translation*

***Theme 1: Increased Efficiency and Productivity***

Participants consistently framed AI as generating a time-compression effect by accelerating first-draft production and automating routine micro-decisions (e.g., segment matching, predictable phrasing, and template-like structures). Notably, "efficiency" was not discussed as speed alone; rather, it was described as a reconfiguration of professional attention, where translators shift from repetitive production toward higher-order activities such as quality assurance, coherence monitoring, audience sensitivity, and domain-appropriate revision. This matters directly to the purpose of the study because it shows that translators evaluate AI not merely as a "translation substitute," but as a workflow technology that changes what counts as valuable expertise in contemporary practice.

For instance, one participant emphasized that AI reduces repetitive labor and frees cognitive resources for evaluative work: "What used to consume my time was rewriting the same patterns repeatedly. Now the system takes care of that repetition, and I invest my effort in judgment-heavy tasks—quality checking, refining the text, and ensuring it reads naturally in the target language" (P6). This quotation illustrates the mechanism through which AI increases productivity: it is not that translators become passive, but that their labor becomes more editorial and diagnostic, focusing on decision quality rather than sheer output volume.

Similarly, another participant described AI as providing a faster "starting point" that supports strategic time management under deadline pressure: "AI doesn't do my job for me, but it delivers a quicker initial draft. When that draft comes earlier, I can plan my time better and still meet tight deadlines" (P10). In analytic terms, this indicates that efficiency is experienced as schedule resilience, particularly in working environments where turnaround is a key performance constraint.

A further account shows the structural implications of this time-compression: "Honestly, my current workload wouldn't have been realistic a few years ago. With AI, I can move through two or three demanding projects in one day—before, that volume would stretch out and exhaust my schedule" (P15). This highlights how AI is perceived to expand professional capacity and throughput, enabling translators to accept more assignments and respond to market pressures—an outcome that directly relates to the "benefits" component of the study's focus.

Importantly, participants' accounts also imply an embedded trade-off: efficiency gains appear to depend on active human oversight, suggesting that productivity is achieved through augmentation (human + AI), not replacement. This theme therefore positions AI as a catalyst for reallocating expertise from mechanical drafting toward quality control and high-level decision-making, which is central to understanding translators' evolving roles in AI-mediated translation environments.

***Theme 2: Cost-Effective Solutions***

Cost effectiveness was discussed as a practical advantage, but also as a site of tension regarding professional value. Participants explained that faster draft generation can reduce production time and allow more competitive pricing—particularly for large-volume projects. However, they also stressed that translation pricing is not reducible to time spent typing; it reflects risk management, interpretive accuracy, accountability, and responsibility for outcomes. This theme is significant to the study's purpose because it shows translators' awareness that AI can reshape not only workflow, but also market expectations and the perceived legitimacy of professional labor.

One participant framed cost efficiency as a mutually beneficial adjustment that preserves profitability: "Because I'm not wasting hours on repetitive segments, I can offer a better price and still keep the job worthwhile. It becomes a win-win—faster delivery for the client and a healthier workflow for me" (P11). This illustrates that cost benefits are often understood as efficiency-driven pricing flexibility, rather than a reduction in professional standards.

At the same time, participants clarified that lower costs should not imply lower expertise. As one noted: "Yes, AI can make the process cheaper, but clients need to understand they're not buying 'speed only.' They're paying for a professional product—accuracy, tone, and responsibility" (P9). This comment directly addresses the study's aim by showing how translators conceptualize the boundary between AI-enabled affordability and the enduring necessity of human judgment.

The same concern is reinforced in a further statement: "The tool reduces some costs, but it doesn't eliminate the real work. I still have to validate meaning, repair weak phrasing, and protect quality—so cost savings should never be taken as 'no expertise needed" (P11). Analytically, these quotations indicate that participants view cost effectiveness as legitimate only when paired with transparent recognition of the human contribution, particularly in high-stakes or reputation-sensitive translation contexts.

In sum, participants perceived AI as enabling more competitive pricing primarily through reduced drafting time, while simultaneously warning that cost narratives can be misused to devalue professional labor. This theme therefore exposes a key socio-economic dimension of AI adoption: cost efficiency is beneficial, but it must be balanced against the preservation of professional accountability and fair valuation.

***Theme 3: Consistency in Terminology***

Participants described AI as functioning as a consistency engine, especially in long documents, terminology-heavy domains, and multi-translator workflows. Terminology consistency was framed as a measurable quality marker that reduces the risk of drift across sections and improves coherence for end-users. This theme is directly relevant to the study's purpose because it demonstrates a concrete, practice-level benefit where AI is perceived as reliably supporting professional standards—particularly in technical, legal, medical, and engineering texts.

One participant explained that AI reduces the likelihood of human slippage under fatigue: "In a long project, consistency is exactly where humans can slip—especially after hours of work. The AI keeps key terms stable, and that saves me from rereading pages just to confirm I didn't change a term halfway through" (P3). This illustrates that the benefit is not merely convenience; it is a reduction of cognitive load and error probability, which is central to professional reliability.

Another participant linked consistency directly to teamwork: "When a team shares the same glossary and memory, the final text feels unified. The tool keeps everyone aligned—so you don't end up with different voices and conflicting terms" (P8). This provides evidence that AI-supported consistency is also a coordination resource, enabling a shared linguistic standard across contributors.

The same point is reinforced through a metaphor that captures AI's non-fatiguing support: "It's like having a memory assistant that doesn't get tired. When the same term appears again, the system retrieves the established choice so the document stays coherent" (P3). In analytic terms, this positions AI as a stabilizer of textual coherence at scale, particularly where repetition and term control are central to accuracy and client satisfaction.

Overall, participants indicated that AI can strengthen terminological discipline and reduce variability—an advantage that becomes especially pronounced in long and collaborative projects. This theme underscores AI's perceived value as infrastructure for standardization, while still assuming the translator's responsibility for context-appropriate selection.

***Theme 4: Enhanced Collaboration***

Participants linked AI to collaboration in two primary ways: translator–translator coordination and translator–client communication. In project teams, AI-enabled platforms were described as shared environments where glossaries, translation memories, and iterative drafts can be synchronized across distance. In client-facing work, AI was perceived to improve transparency by making translation choices more discussable, especially during revision cycles. This theme supports the study's purpose by showing that translators perceive AI not only as a productivity tool, but also as a social-organizational mediator within professional translation workflows.

For example, one participant described how AI-supported tools helped a geographically distributed team stay aligned: "I worked on a multilingual project with teammates in three different countries, and AI tools helped us stay coordinated. Even remotely, shared resources kept the workflow surprisingly smooth" (P2). This quote evidences AI's role as a coordination layer that reduces friction, enabling distributed teams to maintain shared standards and project continuity.

Another participant highlighted how AI can support explanation and negotiation with clients: "When clients ask for changes, I can point to what the tool suggested and then explain the revisions I made. It helps them see the rationale rather than treating edits as arbitrary" (P16). This clarifies the practical mechanism through which AI affects collaboration: it offers a visible "trace" that can be used to justify professional decisions and manage expectations.

A further statement reinforces collaboration as structured alignment rather than informal communication: "The collaboration benefit is real: shared suggestions, shared term choices, and faster alignment. It's less back-and-forth and more coordinated decision-making" (P2). Analytically, these accounts indicate that AI is perceived to support collaboration by standardizing reference points (glossaries, memory, suggestions) and improving the transparency of decision processes.

In summary, participants viewed AI as strengthening collaborative infrastructures—both within translator teams and across translator–client relationships. This benefit, however, remains dependent on human editorial authority, reinforcing the broader finding that AI is valued most when integrated as a support system rather than treated as a final decision-maker.

### *4.2. Risks of AI in Translation*

#### *Theme 1: Lack of Cultural Sensitivity*

Participants repeatedly described cultural sensitivity as a point where AI performance becomes unstable. While AI may reproduce dictionary-level meanings, participants argued that it often fails in pragmatics, tone, cultural resonance, and the recreation of intended effect—particularly in creative genres such as literature, marketing, and humor. This theme is crucial to the study's purpose because it identifies a boundary condition: where translation is fundamentally about meaning-in-culture rather than sentence-level equivalence, participants see AI as limited.

One participant explicitly contrasted technical adequacy with cultural failure: "For technical writing, AI may be acceptable, but for culturally saturated texts it often misses what the message is really doing. It transfers words, not the emotional and cultural logic behind them" (P12). This demonstrates that participants distinguish between "semantic transfer" and culturally appropriate translation, indicating a nuanced professional understanding of translation quality.

Another participant illustrated the issue through humor, where literalness breaks communicative impact: "I had a case where humor was the core of the message—and the AI flattened it. The output was literal and stiff, and the joke disappeared, so I had to rebuild the effect from the ground up" (P7). This underscores that AI's limitation is not only linguistic but rhetorical: it may fail to preserve the function of the source text in the target culture.

Participants also framed cultural limitation as a source of client misunderstanding and workflow disruption: "Clients sometimes assume the tool can handle everything. Then the translated text fails to connect with real readers, and they return because the message didn't travel" (P19). This clarifies the applied consequence: cultural insensitivity does not remain a theoretical flaw; it becomes a practical problem that generates revision cycles and reputational risk.

Overall, this theme indicates that participants locate AI's most consequential weakness in its limited capacity to model culture, voice, and audience reception—precisely the dimensions central to professional translation in creative and persuasive contexts.

***Theme 2: Over-Reliance on AI***

The theme of over-reliance captured participants' concern about cognitive offloading and potential skill erosion, alongside client expectations that AI output should be treated as authoritative or sufficient. Participants cautioned that over-reliance can produce two risks: declining quality due to insufficient verification and the devaluation of human expertise through "AI-only" demands. This theme supports the study's purpose by revealing that perceived risk is not just technical—risk is also behavioral and market-driven.

For example, one participant observed that reliance can become a shortcut that weakens checking practices: "I'm not against AI, but I've seen translators treat it like a shortcut. If you don't verify carefully, errors slip in—sometimes basic ones that a trained translator would normally never allow" (P18). This quote shows that participants perceive quality as dependent on sustained professional vigilance, not on tool output.

Another participant highlighted client-driven reliance: "Some clients tell me, 'Use AI, don't translate it yourself.' It's strange—people are quick to trust a machine, yet hesitant to trust a professional translator" (P4). This illustrates how over-reliance can be socially produced through client ideologies, which can pressure translators toward minimal intervention.

A final quotation clarifies the mechanism of failure: "The issue isn't the tool itself; it's the habit of accepting the output too easily. When verification disappears, quality becomes accidental" (P18). Analytically, this theme emphasizes that AI risk is partly a matter of professional practice norms and expectation management—highlighting the need for clear guidelines and human-in-the-loop standards.

***Theme 3: Post-Editing Fatigue***

Participants described post-editing fatigue as a paradox: AI may speed up drafting but can intensify the cognitive burden of correction. The fatigue stems from continuous micro-revisions, unnatural phrasing, and subtle errors that require sustained attention. This theme is relevant to the study's purpose because it complicates simplistic "efficiency" narratives by showing where time savings may be partially offset by editorial strain.

One participant summarized this tension: "Some days it feels like I spend longer repairing AI output than I would translating directly. The workflow becomes correction-heavy and surprisingly draining" (P14). This signals that post-editing is not always a lighter task; it can be more exhausting due to persistent error monitoring.

They further explained the mechanism: "The tool makes small missteps again and again—so you're trapped in constant revision mode. That kind of work is mentally exhausting because you can't drop your attention for a second" (P14). This highlights the cumulative nature of fatigue: even minor issues become significant when repeated across large texts.

Finally, the same participant emphasized stylistic unnaturalness as a key contributor: "I often rewrite entire sentences because the AI version reads unnatural—technically close, but not human in rhythm or style" (P14). This clarifies that fatigue is driven not only by accuracy errors but also by the effort required to restore readability and genre-appropriate voice.

In sum, post-editing fatigue emerges as a cost of AI integration that can affect translators' well-being and the true productivity of AI-assisted workflows, reinforcing the need to evaluate "efficiency" across the entire translation lifecycle, not only the drafting stage.

***Theme 4: Ethical Concerns***

Ethical concerns were framed as pragmatic risks: data privacy, confidentiality, ownership, and economic displacement. Participants expressed uncertainty about what happens to texts uploaded to AI platforms and worried about the implications for professional security and fair compensation. This theme directly supports the study's purpose by showing that translators evaluate AI not only on output quality, but also on institutional trust and labor-market stability.

One participant highlighted confidentiality anxiety: *"I hesitate with confidential files. Once you upload sensitive documents, you don't truly know where that information goes or how it might be stored"* (P8). This illustrates the perceived governance gap in current AI tool use, particularly relevant in legal and medical translation contexts.

Another participant connected AI adoption to pricing and job security: *"AI is pushing prices down, but we have to ask what we're trading away. If the market treats AI as a replacement, professional translators may lose fair income and long-term security"* (P11). This establishes that ethical concern includes economic vulnerability and professional sustainability.

They further concluded: *"Even if AI improves efficiency, it can undercut the profession—especially when clients confuse tool output with professional accountability"* (P11). Analytically, this theme suggests that ethical questions are inseparable from accountability and fair valuation, implying the need for clearer standards and professional protections.

***Theme 5: Technical Limitations***

Participants noted persistent technical limitations in handling ambiguity, layered meaning, dense syntax, and context-*dependent* interpretation. These limitations were frequently referenced in legal and literary translation, where coherence depends on discourse-level reasoning and genre knowledge. This theme matters to the study's purpose because it identifies where AI's linguistic competence may appear fluent yet still fail at interpretive correctness.

One participant explained: *"When a sentence carries layered meaning, the system doesn't really read between* the *lines. It picks one surface interpretation and treats it as the whole story"* (P5). This indicates that AI struggles with pragmatic inference and interpretive plurality—key competencies in advanced translation.

They also noted domain sensitivity: *"In legal and poetic texts, the output can sound robotic—like it doesn't grasp the context that a human translator immediately considers"* (P5). This clarifies that limitation is not only semantic but stylistic and contextual.

Finally: *"Complex structures and long passages expose the limits quickly; you end up doing heavy intervention because the machine can't sustain coherence the way a human reader-writer can"* (P5). This supports the finding that technical limitations surface most clearly in sustained discourse, requiring substantial human correction to restore coherence and intent.

### *4.3. Future Pathways of AI in Translation*

***Theme 1: AI as a Complementary Tool***

*Participants overwhelmingly articulated a division-of-labor future in which AI supports repetitive or low-risk tasks while humans remain responsible for high-stakes meaning, contextual calibration, and quality assurance. This theme is central to the study's purpose because it frames the perceived "future" not as replacement but as augmentation.*

*One participant stated: "I see AI as support, not substitution. Let it handle the mechanical parts quickly, but the sections where accuracy and context matter still require a human translator's judgment"* (P1). This shows that participants envision future competence as knowing where AI is appropriate and where human control is essential.

They added: *"Some texts don't require extreme precision everywhere—but the moment a passage becomes sensitive or high-impact, a human should take control and translate it directly"* (P1). This clarifies the operational model participants expect: selective reliance, guided by risk and impact.

Finally: *"For me, the future is collaborative: AI accelerates simple tasks, and the translator safeguards meaning, tone, and accountability"* (P1). Analytically, this positions AI as infrastructure for speed, with humans as custodians of responsibility and quality.

***Theme 2: Specialization in Creative Tasks***

Participants predicted increased specialization in areas where AI remains weak: transcreation, literary translation, culturally embedded narratives, rhetorical adaptation, and creative writing. This theme advances the study's purpose by identifying how translators expect professional identity and value to evolve under AI conditions.

One participant noted: *"When a novel includes socio-cultural references, you need social knowledge to carry meaning across. AI tends to miss that message or flatten it"* (P3). This demonstrates that creative translation is seen as culturally situated work rather than lexical substitution. Another added: *"Translation isn't only meaning transfer. The hard part is artistry—emotion, imagination, creative choices—and that's where I don't see AI matching a human translator"* (P6). This clarifies why specialization is anticipated: translators expect the market to increasingly value what AI cannot consistently reproduce.

They further concluded: *"AI can draft a version, but it doesn't reliably recreate the cultural effect. In creative work, the translator becomes a re-author, not a re-typist"* (P6). This supports the interpretation that translators foresee a shift toward creative mediation and cultural authorship.

***Theme 3: Enhanced Collaboration***

Participants anticipated more interactive AI systems functioning as real-time co-pilots integrated into decision-making, reducing fragmentation between drafting and editing. This theme aligns with the study's purpose by showing how participants envision future tools as more collaborative but still subordinate to human editorial authority.

One participant predicted: *"What I expect next is a co-pilot tool—supporting you in real time as you translate, so the workflow becomes smoother"* (P15). This indicates that participants value AI most when it reduces friction and supports continuous decision-making.

Another described AI as an opportunity contingent on human responsibility: *"AI will likely* become *a primary assistant for professionals. It's not a threat by default; it becomes an opportunity if the human remains responsible for the high-value decisions*" (P11). This reinforces the human-in-the-loop expectation for future professional practice.

Finally, *"If the tool takes care of routine load, the translator can concentrate on meaning, style, and risk—so collaboration becomes the core design of next-generation systems"* (P15). Analytically, this theme suggests that participants expect AI development to move toward deeper workflow integration rather than isolated machine output.

***Theme 4: Ethical and Regulatory Frameworks***

Participants emphasized governance as a necessary condition for sustainable AI adoption, calling for ethical codes, liability standards, privacy protections, and clear rules on ownership and compensation. This theme contributes to the study's purpose by demonstrating that future "venues" are institutional as well as technological.

One participant stated: *"If AI stays in the workflow, we need rules—real protections for clients and translators. Without standards, things become chaotic quickly"* (P10). This indicates that trust in AI is conditional on enforceable safeguards.

They highlighted unresolved rights issues: *"Ownership and compensation are still unclear—who owns AI-assisted output, and how should that affect fair payment?"* (P10). This directly links governance to labor fairness and intellectual property.

Finally, they raised accountability*: "If AI introduces an error in a legal or medical text, we need clear guidance on responsibility—otherwise the risk falls back on the translator"* (P10). Analytically, this theme frames regulation as a mechanism for aligning innovation with responsibility—an essential requirement for professional adoption in high-stakes translation settings.

Taken together, the findings depict AI as a dual-impact infrastructure: it enhances efficiency, cost flexibility, terminology control, and collaboration, while simultaneously intensifying cultural, cognitive, technical, and ethical vulnerabilities. Participants' accounts converge on a hybrid professional future in which translators' competitive advantage is increasingly anchored in human-led judgment—cultural calibration, creative specialization, rigorous verification, and ethical risk management—supported (but not replaced) by AI-enabled tools and strengthened by clearer regulatory frameworks.

## 5. Conclusion

This study indicates that translators experience generative and AI-enabled translation as a dual-impact infrastructure: it compresses production time and strengthens procedural consistency, yet it simultaneously introduces new fragilities in cultural-pragmatic fidelity, verification norms, cognitive load, and accountability. The core pattern is not replacement but reorganization: AI shifts the locus of expertise from drafting to judgment, elevating the value of quality assurance, cultural calibration, and risk management. In that sense, the "next era" is best characterized as conditional augmentation in which adoption is rational only when human oversight is deliberate, role boundaries are clear, and quality is evaluated in terms of purpose and consequence rather than surface fluency alone.

For professional practice, the findings argue for risk-tiered workflows and explicit verification protocols that counter over-reliance and automation bias. Agencies and freelancers can operationalize this by defining when AI drafting is acceptable, what minimum checks are mandatory (terminology, numerals, negation, modality, discourse relations), and which domains require stricter human control due to privacy or liability exposure. For translator education, the results support curricula that treat AI as part of competence: prompt literacy, error taxonomy, post-editing ergonomics, and ethical reasoning around confidentiality and ownership should be taught as assessable skills—not informal survival tactics. For tool design and governance, the study implies that sustainable adoption depends on transparency features (audit trails, data-handling clarity, and controllable settings) and on professional standards that clarify responsibility allocation when AI is used in high-stakes texts.

The study is limited by its qualitative scope, small sample (N = 20), and sample composition, which may reflect regional, language-pair, and market-specific patterns that are not generalizable. The task-based, remote design improves ecological realism compared with interview-only approaches, but it still cannot fully replicate client pressure, confidential materials, or long-horizon project dynamics that shape real-world decision-making. In addition, the frequency table reported "quoted participant" representation, which is a transparency device rather than a prevalence measure and should not be interpreted as a definitive ranking of importance. Future research should extend this work through multi-site and cross-linguistic sampling (including low-resource language contexts), explicit inclusion of translation educators as curriculum gatekeepers, and longitudinal designs that track how verification habits, fatigue, and pricing norms evolve under sustained AI use. Mixed-method studies that combine workflow observation with quality evaluation sensitive to pragmatics and discourse coherence would be especially valuable for moving from perceived pathways to demonstrably reliable pathways.

**Authors' Contributions**

All authors contributed significantly to the research process.

**Declaration**

We affirm that the manuscript is original and has not been previously submitted or published in any journal.

**Transparency Statements**

The data that support the findings of this study are presented within the article; any additional data are available from the corresponding author upon reasonable request.

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The study adheres to the ethical standards set forth by the Committee on Publication Ethics (COPE).

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