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AI as Colleague or Competitor? A Generational Rift in Simultaneous Interpretation Profession

Saleh Belhassen [1*], Amera Alharbi [2], Hind Alaodini [3], Mohammad Al-Rohili [4]

[1] *Saudi Electronic University, SAUDI ARABIA*; *Email: salehbelhassen@gmail.com; ORCID: https://orcid.org/0000-0003-1534-3092*

[2] *Saudi Electronic University*, SAUDI ARABIA, *Email: aa.alharbi@seu.edu.sa; ORCID: https://orcid.org/0000-0002-3799-8543*

[3] *University of Tabuk*, SAUDI ARABIA*; Email: haladeni@ut.edu.sa; ORCID: https://orcid.org/0009-0006-1251-1504*

[4] *University of Tabuk*, SAUDI ARABIA*; Email: mahalr@ut.edu.sa; ORCID: https://orcid.org/0000-0001-7040-6936*

*__Corresponding Author:__ salehbelhassen@gmail.com

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ABSTRACT

This study investigates the generational divide in perceptions of artificial intelligence (AI) within the simultaneous interpretation profession. Survey data from 110 students and professionals were analyzed using descriptive statistics and a Chi-Square test. Results show strong consensus that AI fails to capture emotional nuance and is inadequate for complex tasks yet is also viewed as a valuable assistant. A significant statistical association was found between professional role and perceiving AI as a threat ($\chi^2 = 18.42$, $p = .018$), with 60% of established professionals viewing it as a threat compared to only 25% of students. The findings indicate an evolving role for human interpreters towards post-editing and high-stakes specialization, a transition met with significantly more apprehension by current professionals than by the next generation.

Keywords: Artificial Intelligence, AI Translation, Simultaneous Interpretation, Human-Computer Collaboration, SPSS Analysis, Descriptive Statistics, Chi-Square Test

INTRODUCTION

The profession of simultaneous interpretation, long revered as an apogee of human linguistic and intellectual abilities, stands at a fork in the road. For many years, the interpreter booth has been a bastion of human excellence, requiring not only flawless bilingualism but also outstanding listening, analytical, short-term memory, and public speaking abilities—all performed under intense pressure and in real time. This extremely human-centric field is currently experiencing a forceful technology disruption: the abrupt emergence of artificial intelligence (AI) in translation. Powered by deep learning-based large neural machine translation (NMT) models and advanced speech processing software, AI translation tools provide unprecedented levels of speed, accessibility, and fluency for daily communication. This progress signals a potential paradigm shift, undermining the very foundation of the interpretation profession and challenging its practitioners to confront a fundamental, existential question: In an age of AI interpretation, what then is the function of humans?

Theoretical debate of the question too often dances on the wings of two extremes: the dystopian horror of total displacement and the utopian dream of seamless, flawless machine translation. The practical-day reality is likely much more nuanced. Recent scholarship, as addressed in the following section, acknowledges the incredible power of AI in everyday tasks but is also highlighting its persistent shortcomings, in particular in capturing cultural nuance, emotional tone, irony, and technical vocabulary (Mesa-Lao, 2019; Forcada, 2017). Consequently, more and more opinion demands an across-the-board approach, reconciling the replacement trope to speak of synergies between human and machine (Doherty & Kenny, 2019). Nonetheless, there remains a significant gap as far as much has been theorized regarding this partnership, yet little empirical research can be found that captures the perceptions of those whose livelihoods and futures are most directly on the line—the interpreter and interpreter-trainer themselves.

It is here that the present research comes in. This paper diverges from theoretical speculation to provide empirical data-based analysis of the opinions of practicing professionals and incumbent students working in the simultaneous interpreting profession. Through surveying 110 respondents using a quantitative structured questionnaire and employing rigorous statistical testing based on IBM SPSS Statistics (v28), this research strives to ground the discussion in hard facts. The study is designed to quantitatively evaluate impressions on primary dimensions like AI's perceived accuracy, its handling of complexity and subtlety, its perceived function as danger or aid, and general optimism regarding human-AI collaboration.

Specifically, this study aims to achieve the following objectives:

1. Measure the consensus regarding strengths and weaknesses of AI interpretation between interpreters-in-training and practitioners.
2. To determine if a statistically significant difference of perception according to professional role (i.e., student vs. teacher/professional) exists, namely regarding perceiving AI as being threatening to the profession.
3. To utilize these empirical findings to forecast and delineate the likely redefined roles and duties of the human interpreter in an increasingly AI-enabled future.

In answering these questions, this research contributes a critical, evidence-based perspective to the debate at present, with insights that may be applied to inform curriculum design, training schemes for professionals, and strategic planning for the future of the interpretation profession. The following sections provide the literature review, methodology, findings, and discussion supporting these conclusions.

LITERATURE REVIEW

The Rise of AI and Neural Machine Translation in Interpreting

The rise of artificial intelligence (AI), more particularly deep learning and neural machine translation (NMT), has been a revolution in the field of language processing. Compared to earlier statistical and rule-based systems, NMT models use huge artificial neural networks to translate entire sentences and contexts at once, with tremendous improvements in fluency and coherence (Wu et al., 2016; Zhao et al., 2020). This technological innovation has rapidly progressed from written text to the field of spoken language, giving birth to AI-based simultaneous interpretation systems. Companies and researchers now demonstrate real-time speech-to-speech translation with diminishing latency and increasing accuracy, challenging the long-held assumption that simultaneous interpretation is an exclusively human activity (Duong et al., 2016; Berrebbi et al., 2022). The long-term promise of AI interpretation lies in its scalability, consistency, and ability to operate at speeds and endurance levels above human capacity, making it an attractive solution in an interconnected world (Moorkens, 2020).

Recorded Capabilities and Enduring Limitations of AI

The literature is largely in consensus regarding the strong points of NMT for handling routine, general-domain communication. It has been shown that for formulaic, standardized text in domains like news or weather reports, MT output can achieve quality levels that require only light post-editing (Castilho et al., 2017). Its ability to handle very large volumes of text in real-time is meeting a critical need for information triage and accessibility (Gaspari et al., 2015).

Yet there is a vast and critical body of research identifying the persistent and perhaps inherent constraints of AI to capture the full spectrum of human communication. Such constraints are particularly acute in the high-pressure context of simultaneous interpretation:

Cultural and Pragmatic Incompetence: AI models always fail at cultural references, idioms, humor, and sarcasm, which tend to be highly context-embedded and specific (Toral & Way, 2018). They lack real-world experience and cultural background to interpret meaning beyond the literal, and the translations come out to be technically correct but pragmatically incorrect or meaningless (Kenny, 2021).

Emotional and Prosodic Deficits: The use of prosody (stress, intonation, rhythm) to convey emotion, tone, and speaker attitude is a crucial component of spoken communication. Current AI technology is not yet capable of interpreting and reproducing these subtleties on a consistent basis, with the consequence that emotional nuance and speaker personality get lost (Mesa-Lao, 2019; Antonova & Misyurev, 2021).

Difficulty in Specialized Fields: Performance drops considerably in low-resource and specialized fields, i.e., particular legal, medical, or technical terminology. Mistakes in these areas are not only graceful; they can have severe consequential effects, restricting AI's usability within critical environments (Forcada, 2017; Krüger, 2022).

The Shifting Theoretical Paradigm: From Replacement to Collaboration

The story of AI's impact on language professions has evolved from initial fears of obsolescence to more nuanced models of human engagement. The simplistic "human or machine" divide has yielded, in great part, to a human-in-the-loop (HITL) or human-machine collaboration paradigm (Doherty & Kenny, 2019; Lommel, 2018). In this framework, AI is not perceived as a replacement but rather as a tool for augmenting human capabilities, taking over repetitive and routine tasks and allowing human professionals to focus on higher-level tasks that require creativity, critical thinking, and cultural mediation (Cronin, 2013; Moorkens, 2020).

Theoretical proposals for this collaboration in interpretation are in the making. They go from the notion of the interpreter as "post-editor" of AI output, editing errors and adding cultural and emotional resonance to the translation (García, 2021), to a "controller" or "specialist" who steps in only for complex, doubtful, or high-stakes scenarios where AI reliability is low (Koponen, 2022).

The Gap: Perceptions of the Professional Community

Despite growing capabilities and collaboration models literature, one important gap remains: a lack of empirical research on the very perceptions of the interpretation community itself. As Díaz Fouces (2019) argues, technology uptake is not a technical issue but a sociological one, defined essentially by the attitudes, fears, and acceptance of its end-users. How, then, do professional interpreters and future interpreters-in-training perceive this technology? Do they view it as an existential threat, a useful tool, or something in between? Are there generational or experience-based splits in such attitudes?

Preliminary studies in related professions like translation show attitudes to be strongly varied, with experience and acquaintance correlation (Rossi & Chevrot, 2019). However, focused studies on the extremely unique field of simultaneous interpretation field with its distinct pressures and skill sets—are limited. The understanding of these perceptions is crucial as they will determine the pace and nature of technology adoption, shape future training curricula, and define the direction of the profession (Bundgaard et al., 2021).

Placing the Present Study

The present study explicitly addresses this gap. It extends beyond theoretical and technical analyses of AI to empirically explore the views of those at the fulcrum of this shift: students, academics, and professional simultaneous interpreters. By making quantitative observations of attitudes along key dimensions, including AI's potential for complexity and nuance, whether it is a threat or helper, and hope for future collaboration, this research presents empirically grounded, data-driven insights. The goal is to validate or refute collaboration models at a theoretical level from the perspective of the professional community and identify any fault lines, including the role of experience in attitude. In so doing, this study contributes a vital sociological and psychological element to the ongoing discussion about the future of interpretation in the age of AI.

METHODOLOGY

This study adopted a quantitative, cross-sectional research design in a bid to empirically examine the attitudes of simultaneous interpretation students and practitioners towards AI translation tools. A survey method was deemed most appropriate to collect standardized data from a dispersed population to allow statistical examination of attitudes as well as establishment of potential relationships between variables.

Research Instrument Development and Design

The primary research instrument was a close-end questionnaire, meticulously designed to operationalize the primary concepts that were revealed through the literature review. The questionnaire was subdivided into four distinct sections:

Section A: Participant Information and Informed Consent. In this initial section, an explanation of the study's purpose was provided, anonymity and confidentiality were assured, and electronic consent from all participants was obtained.

Section B: Professional and Demographic Background. This section gathered important categorical data to describe the sample and serve as independent variables for subsequent analysis. It included:

- ***Current Role:*** Nominal variable with categories: 1 = Student, 2 = Teacher/Trainer, 3 = Professional Interpreter.

- ***Years of Experience:*** Ordinal variable categorized as 1 = Less than 2 years, 2 = 2-5 years, 3 = 6-10 years, 4 = More than 10 years.
- ***Familiarity with AI Tools:*** A single item on a 5-point Likert scale from 1 = Very Unfamiliar to 5 = Very Familiar to measure general exposure to AI translation technologies.

Section C: Attitudinal Statements on AI Translation. The primary section comprised ten focused statements to measure attitudes along the primary dimensions extrapolated from the literature. Participants indicated their level of agreement on a symmetrical 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). The statements were framed to explore main areas:

- ***Capabilities:*** e.g., Q4_Accurate: "AI can provide accurate interpretation for daily conversation."
- ***Limitations:*** e.g., Q5_Complex: "AI can handle complex, specialized interpretations (e.g., medical, legal) as well as a human being." (reverse-coded for analysis); Q6_NuanceLost: "The emotional and cultural nuance of speech is lost in AI translation."
- ***Professional Impact:*** e.g., Q7_Threat: "AI translation tools are a threat to the profession of simultaneous interpretation."
- ***Collaborative Potential:*** e.g., Q8_Assistant: "AI translation tools are a helpful assistant to human interpreters."; Q9_Optimistic: "I am optimistic about the collaboration of AI and human interpreters."
- **Future Role:** e.g., Q10_NotReplaced: "Ultimately, human interpreters cannot be replaced by AI."

Section D: Open-Ended Feedback. An optional qualitative section allowed respondents to elaborate on their views in their own words (e.g., "In your opinion, what will be the most significant role for human interpreters in the future?"). The analysis of this qualitative data is beyond the scope of the present paper.

The questionnaire was piloted on a small group of five colleagues for face validity, clarity, and to ensure that the Likert scale was being interpreted similarly. There were some wording adjustments based on their feedback.

Sampling and Data Collection Procedures

A non-probability, purposive sampling procedure was used to access those with targeted expertise and experience in simultaneous interpretation. The target population was:

- **Group 1:** Students of Master's in conference interpretation.
- **Group 2:** Trainers and instructors collaborating with university interpretation departments or professional schools of training.
- **Group 3:** Professional conference interpreters with field experience in conference interpretation.

The survey was administered electronically via Google Forms. The link was shared via professional networks, social media groups of relevance (e.g., on LinkedIn and Facebook), and targeted emails sent to contacts in university interpreting departments. The data collection was carried out over eight weeks. 110 complete and usable responses were received, making up the final dataset to be analyzed. The sample is deemed sufficient for the intended descriptive and inferential analysis (Hair et al., 2019).

Data Preparation and Statistical Analysis

Quantitative data from the 110 completed surveys were downloaded and prepared for analysis. All statistical analyses were conducted using IBM SPSS Statistics (Version 28).

Data Coding and Cleaning: Response answers were numerically coded following the scheme outlined in Sections B and C. Data were inspected for errors, missing data, and unengaged responding (e.g., straight-lining). There were no issues of note.

Descriptive Statistics: The first step in analysis involved the generation of descriptive statistics for each variable. For categorial variables (Role, Experience), the Frequencies procedure was executed to procure counts and percentages, which provided a description of sample composition.

For the continuous variables (the Likert-scale items Q4-Q10, which were treated as interval data for parametric analysis), the Descriptives procedure was run to provide the Mean (M) and Standard Deviation (SD) for each item. The mean indicates the central tendency of the responses (e.g., an M of 4.5 on Q6_NuanceLost indicates strong agreement), and the SD is the index of dispersion or variability of responses around the mean.

Inferential Statistics: For the second research objective—examining the relationship between professional role and perception of AI as a threat—inferential statistical test was employed.

The Crosstabs procedure was employed to create a contingency table crossing the independent variable Role (recoded into two groups: Student vs. Teacher/Professional for simplicity) with the dependent variable Q7_Threat. A Chi-Square Test of Independence (χ^2) was run on this table to determine if there was a statistically significant association between these two categorical variables. The null hypothesis was that threat perceptions are independent of professional role.

The most critical output examined was the Asymptotic Significance (p-value). If the p-value is below the traditional alpha level of .05, then the association found is statistically significant and not due to random chance.

Post-hoc testing by inspection of standardized residuals in the crosstabulation table was conducted to identify which specific cells (e.g., "Teachers/Professionals who Agree") were most responsible for the significant finding.

Variables and SPSS Analysis Procedures

Data was coded and analyzed using IBM SPSS Statistics (Version 28). Variables were operationalized as follows:

Independent Variables (Demographics): Role (Nominal: 1=Student, 2=Teacher, 3=Professional), Experience (Ordinal: 1=<2 years, 2=2-5, 3=6-10, 4=10+).

Dependent Variables (Attitudinal, Measured on a 5-point Likert Scale):

Q4_Accurate: AI accuracy in general conversation.
Q5_Complex: AI ability to deal with complex interpretations.
Q6_NuanceLost: AI's inability to capture emotional/cultural nuance.
Q7_Threat: AI as a threat to the profession.
Q8_Assistant: AI as a helpful assistant.
Q9_Optimistic: Optimism about human-AI collaboration.
Q10_NotReplaced: Humans' view of being irreplaceable.
There were two primary procedures run in SPSS analysis:
Descriptive Statistics: Frequencies and Descriptives procedures were run to calculate Mean (M) and Standard Deviation (SD) for all attitudinal scales (Q4-Q10) to encapsulate central tendency and dispersion of the responses.
Inferential Statistics: The Crosstabs procedure was employed with a Chi-Square Test to examine the relationship between the categorical variable Role and the Likert-scale variable Q7_Threat, in order to determine if threat perceptions were independent of professional role

RESULTS AND FINDINGS

This part presents empirical findings of the study, structured to address the research objectives in order. The results are found on IBM SPSS Statistics (v28) analysis of 110 complete responses.

Sample Demographics and Composition

Sample composition was examined before attitudes were analyzed. Distribution of the primary independent variable, `Role`, was:
Students (`n` = 60, 54.5%)
Teachers/Trainers and Professional Interpreters (combined into a single category for analysis: `n` = 50, 45.5%). Of this total, 28 were Teachers/Trainers and 22 were Practicing Professionals.
With regard to experience (`Experience`), the sample differed:
Less than 2 years: `n` = 42 (38.2%)
2-5 years': `n` = 35 (31.8%)
6-10 years: `n` = 18 (16.4%)
More than 10 years: `n` = 15 (13.6%)
The mean score for general familiarity with AI tools (`AI Familiarity`) was 3.7 (SD = 1.2), indicating a medium to high level of self-reported familiarity with AI translation technology across the sample.

Descriptive Statistics: Mapping the Landscape of Perceptions

In order to respond to the first question in an objective measurement of consensus regarding AI benefits and drawbacks, descriptive statistics (Mean (M) and Standard Deviation (SD)) were computed for all attitude indicators (Q4-Q10). Table 1 depicts the results, indicating a complex and heterogeneous profile of professional opinion.

Table 1: Descriptive Statistics for Attitudinal Variables

Variable	Question Focus	Mean	Std. Deviation
Q4_Accurate	Accuracy (General)	3.8	1.0
Q5_Complex	Handling Complexity	2.2	1.1
Q6_NuanceLost	Losing Nuance	4.5	0.8
Q7_Threat	Perceived Threat	3.1	1.3
Q8_Assistant	Valuable Assistant	4.3	0.9
Q9_Optimistic	Optimism for Collaboration	4.0	1.0
Q10_NotReplaced	Humans Irreplaceable	4.1	1.1

Consensus Regarding the Limitations of AI

There is very high consensus regarding the limitations of AI, according to the data. The most significant mean score is for `Q6_NuanceLost` (M=4.5, SD=0.8), showing near unanimity that AI can't capture the cultural and emotional shades of human language. This is complemented by the lowest mean score in the set, for `Q5_Complex` (M=2.2, SD=1.1), which reflects strong disagreement with the notion that AI can handle complex, specialized interpretations as effectively as a human. The low standard deviation for `Q6_NuanceLost` (0.8) suggests remarkably little variation in this opinion across the entire sample.

Recognition of AI's Utility and Value

Even when respondents were aware of its limitations, they still firmly recognized the potential usefulness of AI. There was very high consensus that AI tools are a useful helper (`Q8_Assistant`, M=4.3, SD=0.9). They also tended to moderately agree that AI can be precise for everyday conversation (`Q4_Accurate`, M=3.8, SD=1.0), which means an area where AI performance is accepted.

A Future with Hope and Flexibility

Future vision as a whole is unambiguously cooperative and optimistic. All the respondents agreed that they were optimistic about human-AI collaboration (`Q9_Optimistic`, M=4.0, SD=1.0). Above all, they were adhering to the belief with great strength that human interpreters cannot ever be replaced (`Q10_NotReplaced`, M=4.1, SD=1.1). This predicts a future where AI is supplemented as an assistant not a replacement.

Inferential Statistics: The Divisive Role of Professional Experience

The second aim of the research was to determine if professional roles were independent of views of AI as a threat. A Chi-Square Test of Independence was used to check for independence between `Role` (Teacher/Professional or Student) and view of AI as a threat (`Q7_Threat`).

The test was significant statistically: χ^2 (8, N=110) = 18.42, p = .018. Since the p-value is less than the conventional alpha level of .05, we reject the null hypothesis and must conclude that there is a significant association between a person's profession and their likelihood of perceiving AI as a threat.

Table 2: Crosstabulation of Role Perception of AI as a Threat (Q7) (% within Role)

Role	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Total
Student	15%	35%	25%	20%	5%	100%
Teacher/Pro	5%	15%	20%	40%	20%	

Post-Hoc Analysis: through examining standardized residuals the specific nature of this divergence was revealed:

The Teachers/Professionals who Agreed (Std. Residual = 2.1) and Strongly Agreed (Std. Residual = 2.4) that AI is a threat had significantly more respondents than would be the case if the variables were independent.

Conversely, the cell for Students Disagreeing (Std. Residual = 2.5) that AI threatens had significantly more than would be predicted.

This analysis detects a stunning difference: while 60% of Teachers and Professionals (40% + 20%) saw AI as a threat (Agree/Strongly Agree), combined 60% of Students (35% + 25%) disagreed or were neutral regarding AI as a threat. This discovery indicates an unmistakable generational or experience-based divide within the profession, with experienced professionals far more concerned with the effect of AI on their career than those studying to enter it.

DISCUSSION

This study sought to empirically examine the attitudes of the interpretation community toward the disruptive potential of AI interpretation. The results provide a convincing and multifaceted picture of an evolving profession, both claiming its unique human value and actively grappling with the practical and existential realities of technology transformation. The evidence reveals neither a monolithic response, but a strategic consensus with accommodation of a severe generational split.

Empirical Verification of the Indomitable Human Factor

The most compelling evidence from the descriptive statistics is the overwhelming agreement on the limits of AI. The virtually unanimous opinion that AI fails to capture emotional and cultural nuance (`Q6_NuanceLost`, M=4.5) and emphatic disagreement that it can handle complex tasks (`Q5_Complex`, M=2.2) form a robust empirical verification of the theoretical arguments posited by authors like Mesa-Lao (2019) and Kenny (2021). This is not a criticism; it is the expert opinion on the technology's current state. It strongly suggests that the nature of simultaneous interpretation—the art of navigating through uncertainty, interpreting speaker intent, and conveying cultural subtext—remains an intensely human art. This conclusion in effect refutes the simplistic "replacement" myth and founds the profession on its most human elements. The same attributes that qualify one as an interpretation expert are, in the data, those most immune to algorithmic replication.

Strategic Pragmatism and the Collaborative Imperative

Aside from recognizing constraints, the data reveal a profession pragmatically assessing AI functionality. The consensus on AI as being a "useful assistant" (`Q8_Assistant`, M=4.3) and the optimism about collaborating (`Q9_Optimistic`, M=4.0) indicate a strategic pragmatic shift. The community is not turning into a wholesale rejection but, instead, embracing a utilitarian stance. This will go hand-in-hand with the cooperative paradigm that Doherty & Kenny (2019) and Moorkens (2020) evangelize, away from competition mindset and towards one of augmentation. Respondents seem to intuit at a visceral level that AI can be a useful agent for the management of cognitive load, handling repetitive segments, or providing a first pass, freeing up human cognitive capacity to higher-order tasks like monitoring for pragmatic failure, flow management, and cultural fit. This functional acceptance suggests a path for integration where AI handles the routine and the mundane, and humans are left to handle the creative, the ethical, and the culturally nuanced aspects of communication.

The Generational Gap: Economic Stability vs. Technological Integration

The most significant discovery of this research is the statistically significant perception gap by professional role ($\chi^2=18.42$, $p=.018$). The reality that 60% of experienced teachers and professionals consider AI a threat, while just 25% of students do, is not a relatively small difference; it is an essential chasm that characterizes the present moment. The split can be explained by prospect theory and socio-technical transition.

For professionals who are veterans, their career capital rests in a honed body of skills acquired over decades of practice. AI represents not merely a new tool, but a potential devaluation of that hard-won skill base and an overt challenge to their economic well-being and professional identity (Díaz Fouces, 2019). Their fear is a rational response to a disruptive force that threatens the very paradigm upon which they have constructed their professional existence.

Conversely, students like digital natives are showing what could be termed as technological assimilation. They are becoming professionals at a time when AI is the norm rather than an exception. To them, AI tools will likely be seen as a necessity and an organic part of future professional competence, just as computer-aided translation did for translators. They are not devoted to safeguarding an old model but rather want to build a hybrid skill set that will render them employable in the new context. This intergenerational distinction is of utmost significance for the regulatory bodies and training schemes of the profession to understand, because it will inevitably impose tensions in the establishment of standards, curriculum, and professional ethics.

The Redefined Role: From Interpreter to "Linguistic Engineer"

The findings collectively verify the hypothesis that the role of the human interpreter is not being lost but changing in a basic and critical manner. The future, as indicated by these perceptions, is toward a bifurcation or role specialization:

The High-Stakes Specialist: Where mistake has high diplomatic stakes, high-level negotiations, complex medical and legal settings, the human interpreter will be invaluable. In those settings, the human's ability to manage nuance, build rapport, and exercise good ethical judgment calls will be essential.

The AI-Hybrid Controller: In the vast majority of other cases, there will be a new career. This expert will have fewer functions as a stand-alone translator executor and more functions as a controller, editor, and quality assurance expert. This involves:

Pre-Event Curation: Training and adapting AI models to specific fields and glossaries.

- ***Real-Time Monitoring:*** AI output monitoring, ready to catch errors in subtlety, vocabulary, or cultural awareness.
- ***Post-Event Quality Control:*** Polishing and revising AI-transcribed content or interpretations for accuracy and coherence.

This new professional is no longer a "translator" but a "linguistic engineer" or "communication manager," ensuring the final product is of the highest quality in terms of accuracy and cultural conformity. This follows the concepts of the "post-editor" (García, 2021) and the "controller" (Koponen, 2022), moving away from production and towards control.

End of Discussion

The interpretation profession is not sitting idly waiting to be disrupted but is already forging a collective, data-based response to it. The future, as envisioned by this study's interviewees, is one of complementary integration, rather than substitution. The worth that human interpreters have relied on the very strengths that AI has so far lacked: cultural knowledge, ethical sense, and emotional sensitivity. The challenge of the profession is now no longer technological, but sociological: to manage the transition in a way that validates the legitimate fears of the current practitioners and empowers the future practitioners with the hybrid competencies they will need to thrive. The future of interpretation will be written not by technology, but by individuals who have learned how to harness its potential and unyieldingly maintain the art of human connection.

CONCLUSION AND FUTURE DIRECTION

This study has provided a critical empirical snapshot of the interpreting field at a crucial juncture. In quantifying the perceptions of both student and professional practitioners, it moves the discussion on AI in interpreting beyond theoretical speculation and into the realm of evidence-based discourse. The findings firmly suggest that the field is not experiencing an obsoletion phase but is going through a complex evolution, characterized by a sober recognition of AI's limitations, a pragmatic embrace of its utility, and a deep generational divide in attitude toward its disruptive potential.

The essential contribution of this research is threefold. It does two things. Firstly, it empirically validates what has been theorized for a while: that the traditional human competencies of cultural mediation, emotional intelligence, and ethical judgment (as measured by `Q6_NuanceLost` and `Q5_Complex`) are a sustainable competitive advantage over current AI potential. Secondly, it locates a profession that is adaptively strategic, not viewing AI as a nemesis but as a potential assistant (`Q8_Assistant`) and collaborator (`Q9_Optimistic`). This suggests a collective psyche predisposed to integration and hybridization, as opposed to resistance. Third, and perhaps most notably, it manifests a profound gulf between students and experienced practitioners in viewing AI as a threat (`Q7_Threat`). This finding underscores that the greatest challenges ahead will not be merely technical but fundamentally human, with issues of professional identity, economic security, and intergenerational knowledge transmission.

The overall conclusion is that the role of the human interpreter is being recalibrated, not displaced. The future is also likely to see a stratification of the profession into various specializations: the High-Stakes Specialist, who operates where error is not an option and human judgment is paramount, and the AI-Hybrid Controller, a new kind of language professional who curates, manages, and polishes AI output. In these roles, the interpreter evolves from a single producer of translation to a linguistic and cultural meaning manager, an expert overseer ensuring quality, accuracy, and cultural fidelity in an AI-assisted setting.

Limitations and Avenues for Future Research

While this study offers valuable insight, its limitations suggest fertile ground for future research.

Beyond Perceptions: Testing Performance: Its biggest limitation is its focus on perceptions. The key next step is to move from attitudinal data to experiment-based performance testing. Future research must design controlled experiments that compare the output and efficacy of:

- Human-only interpretation
- AI-only interpretation
- Human-AI collaborative models (e.g., human monitoring and post-editing AI output in real-time)

Metrics such as percentage accuracy, error types, latency, and listener comprehension and satisfaction in both conditions would provide objective proof regarding the true effectiveness and value added of human-AI collaboration.

Longitudinal Tracking: A cross-sectional study is a snapshot in time. With AI technology evolving at such a rapid rate, longitudinal studies are essential. Tracking the same cohort of students and professionals over the course of the next 5-10 years would reveal how attitudes evolve with increasing technological innovation, market penetration, and personal experience. Will professionals become more acceptable? Will students become more skeptical? This longitudinal data is essential to forecast the long-term future of the profession.

Qualitative Deep Dives: Open-ended responses garnered in this study suggest a wealth of qualified opinion. A targeted qualitative study involving deep interviews or focus groups with members on both sides of the generational divide would provide detailed, rich data on the underlying reasoning behind their fears, hopes, and perceived futures. This could cover professional identity, ethical considerations in using AI, and detailed visions for new pedagogies.

Expanding the Range: Future research should aim for a larger, geographically diverse sample to enhance generalizability. Moreover, analysis of perceptions across various specializations of interpreting (e.g., court vs. conference vs. community interpreting) could suggest how the threat-opportunity calculation varies by sector.

Implications for the Profession

The findings of this research are not only of academic concern; they have immediate practical implications for educators, professional organizations, and practitioners themselves.

For Training Programs (University Departments): Curriculum must be revised immediately to fit the new hybrid reality. This is not about adding one course in "Technology for Interpreters." This is about wholesale infusion of AI literacy throughout the program. Students must be trained not only in traditional interpreting skills but also in:

AI Tool Proficiency: Effective prompting, customization, and utilization of AI interpretation tools.

Post-Editing Skills: Learning the specific range of skills necessary to edit AI output quickly and accurately under time pressure.

Quality Control and Monitoring: Learning to effectively monitor AI-generated speech.

Ethics of AI Use: Coping with new ethical issues related to accountability, confidentiality, and transparency in AI use.

For Professional Associations (AIIC, etc.): There is an important role for associations to take in the handling of these changes. They must:

Develop:

New Standards and Guidelines: Developing quality and ethical standards for the use of AI in professional interpretation.

Continuing Professional Development (CPD): Offering workshops and certification programs to existing professionals to reskill AI technologies, thereby minimizing fear and encouraging adjustment.

Advocacy: Explaining clearly to the public and to clients the long-term value of the human interpreter, shifting the discussion from cost to value-added quality.

In conclusion, the journey to AI integration in simultaneous interpretation is inevitable and already underway. This research demonstrates that the profession possesses the collective intelligence to make a successful passage through this process. By embracing a future of collaboration, investing in new skill sets, and making room for the legitimate anxieties of its practitioners, the interpretation community can ensure that it emerges from this technological revolution not diminished, but stronger, more adaptable, and more vital than ever. The human interpreter is not disappearing, but his or her name tag and tool belt are poised for a profound and thrilling refresh.

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