# AI-Supported Translation Systems for Cross-Cultural Communication

**I Putu Eka Indrawan[1*] and I Made Citra Wibawa[2]**

[1*]Lecturer, Faculty of Science and Technology, PGRI Mahadewa University of Indonesia, Denpasar, Indonesia. E-mail: putueka@mahadewa.ac.id, Orcid: https://orcid.org/0000-0003-2431-7603

[2]Associate Professor, Department of Primary Teacher Education, Faculty of Education University, Ganesha University of Education, Singaraja, Bali, Indonesia. E-mail: imadecitra.wibawa@undiksha.ac.id

***Abstract**:* Translation support systems driven by artificial intelligence are becoming a means of achieving intercultural communication in many areas, including education, business, and public services, that cannot simply substitute words, but help convey meaning and tone in a culturally sensitive way. The present article investigates the rationale behind the design, the architecture, and the outcomes of an AI-based translation system that was created to help instructors working in English with students of different languages in a higher education context. In order to reach this goal, a quasi-experimental design with mixed methods was employed. In a period of nine weeks, twenty instructors made use of the translation system to organize communication with students, while another group of twenty instructors continued to use conventional translation support. The data were collected via a number of means, including surveys, communication logs, feedback forms, and semi-structured interviews, and were analyzed. The findings showed that the group of instructors that used the AI-powered system managed to communicate better than the second group of instructors at the same time. Moreover, students expressed satisfaction with the system in terms of the tone and cultural adaptation of the messages received. The provided architecture comprises a linguistic translation engine, a layer of cultural contextual adaptation, a system for human review, and a feedback loop. The article outlines various practical implications as well, including the risk of oversimplifying culture, the need for human monitoring of sensitive translations, and differences in the reliability of tone detection in various languages. The article concludes by adding that AI-supported translation systems can enhance intercultural communication if cultural calibration and human monitoring are treated as vital factors during the process of development, along with a further need for increased coverage and longitudinal evaluation of the systems.

***Key Words:*** artificial intelligence, machine translation, cross-cultural communication, cultural adaptation, natural language processing, human-AI collaboration, multilingual education

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## Introduction

### Background and Rationale

Today, cross-cultural communication is increasingly using digital tools that not only overcome the language barrier but also the cultural layer embedded in language, a need that has stimulated decades of research on the design of technology-supported communication environments, ranging from early PLEs that aim at supporting autonomous, learner-directed interaction with digital resources to the more recent design frameworks that specifically focus on supporting cross-cultural exchange by means of computation (Haworth, 2016; Zhou et al., 2021). In the field of language education, AI has emerged as a new field of interest and has been applied in translation-related practice in recent years, for example, in applying AI technologies to scaffold students' growing translation competence in higher education English instruction (Cheng, 2022).

Literary texts, in particular, are very challenging for translation technologies because it may contain culturally specific information such as idiomatic expressions that do not lend themselves to literal translation, as reflected in the studies on the translation of culture-specific items in literary classics (Sepehri et al., 2021). Vocabulary support tools, pronunciation assistance tools, and everyday forms of instructional communication require a significant amount of vocabulary and pronunciation assistance, and research on the use of mind-mapping software in vocabulary learning and the role of podcasts in pronunciation training demonstrates the extensive landscape of tools that support the learning process and that are already becoming a part of the instructional communication toolkit in multilingual classrooms (Alahmadi, 2020; Al-Harbi, 2019).

Beyond vocabulary and grammar, there are numerous other elements of language and discourse that AI-powered translation tools must be able to manage. A corpus-based study of the discourse markers of national newspaper traditions showed that there are systematic cultural differences in the use of rhetorical conventions, which are often not preserved when translating literally (Thamer, 2021). Likewise, research on the authorial stance demonstrated in the use of first-person pronouns in English research writing and on the linguistic cues used to mark self-references in English and Persian academic texts shows that even in what are seemingly neutral academic registers, there are culturally-specific practices of stance taking that must be understood and learned by a translation system, rather than being reduced to one default mode (Cui, 2021; Firdaus et al., 2021). The perceived usefulness of any communication tool that uses AI is heavily dependent on how well it fits users' learning and communication styles, which is also supported by motivational research of technical students to understand the impact of learning styles on interaction with learning strategies (Barruansyah, 2018).

This paper can also be seen as a contribution to the research on the use of AI in translation for cross-cultural communication by introducing a conceptual architecture that combines a linguistic translation engine, a layer for cultural-context calibration, a human-review interface, and a continuous feedback loop to enhance the quality and contextual relevance of the translation. It presents empirical evidence based on a quasi-experimental pilot study of nine weeks with two groups of instructors: one group using the proposed system and a second group using a conventional translation system without the cultural adaptation support. Moreover, it highlights some practical challenges such as the potential for cultural oversimplification, the need for human mediation, and different levels of accuracy in tonal detection, relevant for institutions that are using AI-assisted technologies for translation. Finally, structured evaluation metrics and user perception insights are provided that can be used for future comparative studies on an AI-based cross-cultural communication system.

This paper proceeds as follows: In Section II, the scholarship relevant to the linguistic, discourse-level, and design concerns involved in the development of an AI-supported translation system is reviewed. The conceptual architecture of the proposed system is presented in Section III. A research design used in the pilot evaluation is described in Section IV. Section V explains the adaptive translation and cultural calibration in the prototype. The results of the pilot study are reported in Section VI. The findings are used to draw an interpretive inference in Section VII. The paper is closed with a summary of insights and directions for future research in Section VIII.

## Cross-Cultural Communication Research Informing AI-Supported Translation System Design

The design of a system for supporting real cross-cultural communication involves research beyond the traditional field of machine translation, such as discourse analysis, communication design, and human-computer interaction. Research comparing the effects of cognitive strategy instruction on reading comprehension and vocabulary acquisition in males and females shows that learners' cognitive processing and retention of the translated or scaffolded language vary with individual and social factors, which suggests that there is a need for an AI-based system that can cope with the differences, rather than assuming a uniform user profile (Sidek & Rahim, 2015). In addition to this work on the individual level, the work on overlap, interruption, and pause in focus group discussions among multilingual undergraduate students shows how conversational rhythm in itself has cultural significance, which is not captured at all by text-based translation systems when translating spoken interaction into written or synthesized output (Habibi et al., 2020).

Listening comprehension studies on digital audio files as a means of supporting the learning of aural skills further emphasize the need to create AI-enabled communication tools that support communication through both spoken and written modes as well, given that misunderstanding often occurs during spoken communication in real time but not during written communication in the future (Ehteshami & Salehi, 2016). Relevant to the feedback mechanisms that are proposed to be included in this study, the study of teachers' and learners' cognition on the provision of corrective feedback on spoken performance revealed that giving corrective feedback without focusing on face-saving and cultural expectation can have a negative impact instead of a positive one on learners' behaviour of confidence in speaking with a direct implication on the way corrective and clarifying prompts are offered by AI-supported systems with cross-cultural exchange (Nhac, 2021).

The feedback loop design proposed in this paper is also informed by collective and/or task-based research. The research on collaborative output tasks and impact on learners' collocation knowledge reveals that iterative, socially situated language production helps learners to retain knowledge better than isolated correction, which means that input processing systems supported by AI would be better received if integrated in a collaborative language production environment instead of just a corrective one. The example of complementary work using computational text-analysis tools to assist in the selection of instructional core texts shows how computational text-analysis tools can assist human decision making without replacing it, which is a design principle that is also directly reflected in the human-review interface proposed in Section III of this paper. Studies of the use of computer word processors as aids to spelling and grammar development with learners also reveal the long history of the use of automated language tools as supports to, rather than replacements for, human linguistic judgment.

The proposed framework is enriched by insights from communication design fields outside of language education. The studies on intentionality in the data sonification of social issues illustrate the impact of intentional design on making a technically mediated message meaningful and appropriately toned to the cultural perception of its audience, which is directly applicable to the calibration of the social perception of translation output with the support of AI (Lenzi & Ciuccarelli, 2020).

Research has shown that co-creation of value in service settings like health care shows that interactions mediated by technology are evaluated not just based on functional accuracy but also on the perceived quality of the co-created value by the provider and consumer, which is applicable to the way in which instructors and multilingual learners co-create successful communication through an AI-enabled middle agent (Lee, 2019). Lastly, the impact of the human voice and the length of the response on observers' assessments of communication have been studied in social networks, showing that tone and phrasing do affect the trust and satisfaction of the audience, thus directly referring to the cultural-context adjustment layer of the system proposed in the present research (Javornik et al., 2020).

Such findings reveal that the AI translation system is capable of improving intercultural communication, provided that cultural calibration and human supervision are used as necessary components of the system. Evidence of clarity in communication and misunderstanding reduction shows that taking into consideration tone, cultural context, and intentions is equally important as taking care of linguistic accuracy. However, it can also be said that AI cannot fully substitute humans in some sensitive communicative situations where adequate context is significant. The effectiveness of using AI for communication is contingent on the combination of automatic linguistic processing and targeted filtering by humans.

## Architecture of the Proposed AI-Supported Translation System

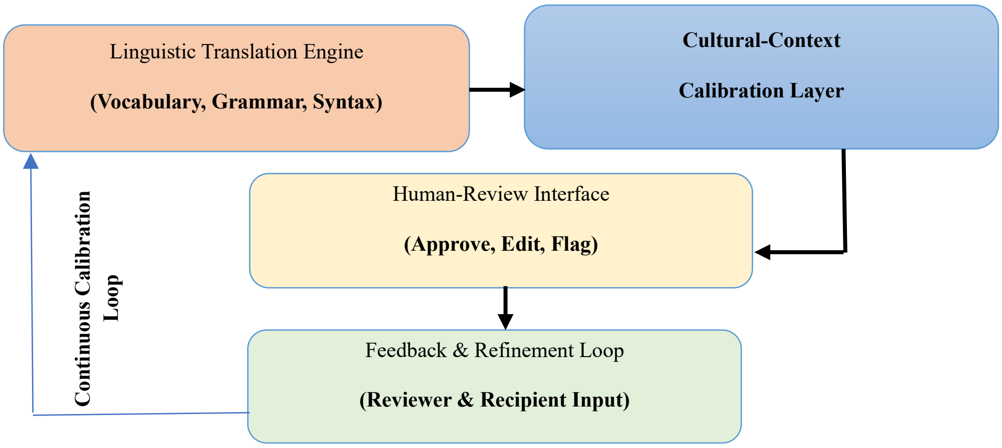


Figure 1: Architecture of the Proposed AI-Supported Translation System

Figure 1 illustrated the design of the system balances the four main components and combines them in a refinement loop. The Linguistic Translation Engine executes the major process of the source language to target language transformation and deals with grammar, vocabulary, and any changes in syntax that might be required in the source written text or the spoken messages. The result of the transformations carried out by the Linguistic Translation Engine is sent to the Cultural-Context Calibration Layer. This layer will modify the tone, level of politeness, and idiomatic expressions to meet the specific communicative context of the recipient and their cultural background, based on knowledge of the relevant norms that exist between the language pairs under consideration.

Later on, the resulting output will go to the Human-Review Interface, which is accessible to any person given the right to supervise the accuracy of the translation, and thus eliminate the possible errors in translations that may relate to sensitive situations. The decisions made by the reviewers, and any feedback from the recipients informing about the mistakes made in the translations, is collected by the Feedback and Refinement Loop, which passes the information back to both the Linguistic Translation Engine and the Cultural Calibration Layer. Thus, the system is given a chance to improve over time as it accumulates the experience from its past applications and adjusts to the particular norms in different communicative contexts.

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## Research Design for Evaluating AI-Supported Translation in Cross-Cultural Contexts

In this research project, which is a quasi-experimental study of the mixed-method type, both system implementation and pilot evaluation in the classroom and workplace were applied for measuring the outcomes of communication quantitatively and for assessing the user experience of AI-enhanced translation technology qualitatively.

The sample included forty lecturers working in a higher education multilingual institution, who frequently communicated with multilingual students via in writing and orally. The lecturers were randomly distributed into an experimental group (number of participants = 20), which used the AI-based translation tool, and a control group (number of participants = 20), which employed the traditional translation methods without adaptation for cultural differences. In addition, some multilingual students participated in the research by providing impressions on the communication received.

The data collection included four instruments in total. The questionnaires were used twice: before and after the study, to assess the extent of self-perceived communication effectiveness. Communication logs included information regarding the number of messages sent and other important notes. The feedback forms provided information about the opinions of students regarding the message. Semi-structured interviews were conducted with a random sample of twelve instructors.

The quantitative assessment by means of the instructors' questionnaires and students' feedback forms allowed researchers to employ descriptive statistics methods. Both qualitative interviews and students' comments on the effectiveness of the messages were analyzed using thematic framing.

## Adaptive Translation and Cultural Calibration Workflow

The prototype system was carried out as a Web-based interface incorporated with the institution's existing messaging platform, enabling instructors to write messages in language and have them translated and culturally adapted before being sent out, while the same is true for the messages received from students.

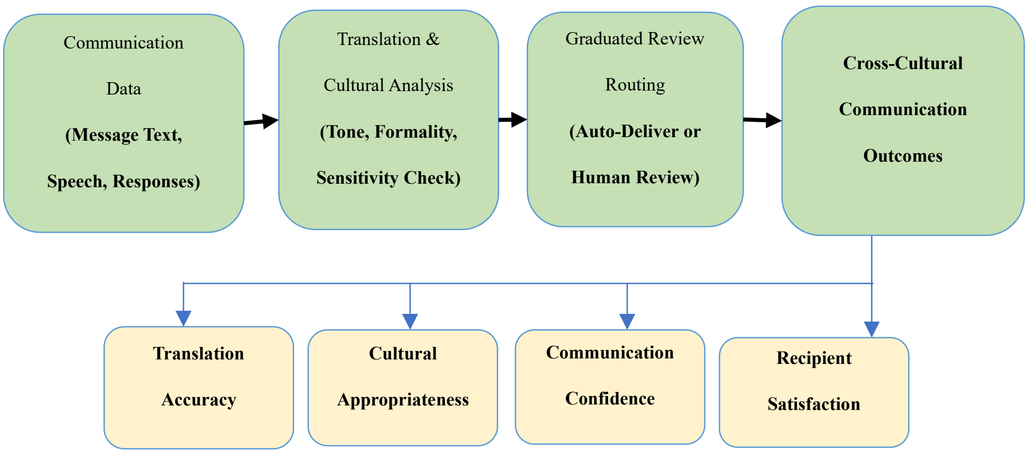


Figure 2: Real-Time Translation and Cultural Adaptation Pipeline

According to figure 2, the first stage in the system's operation includes the gathering of communication data consisting of message text, voice translation, and pattern of response, which is passed through the translation and cultural-analysis system, where the translation not only becomes linguistically accurate but the tone and level of formality are determined. Most critical (sensitive) messages will be sent for human review before sending, while routine messages will go through a lighter mode of automated recalibration based on rational use of resources.

In the course of the process, record the reviewer's adjustment of tone, phrasing, and rejection of translation and use these records for further calibration of communications made by this reviewer with a given group of students. In addition to this, incorporated safeguards against automation covering also such critical cases as emotionally charged and evaluative messages – all of them are subject to mandatory human review regardless of the confidence rating of the system. In short, the workflow described above should achieve results that can be measured against four dimensions – the accuracy of translation, the level of cultural communication, the reliability of communication, and the level of satisfaction of the receiver with communication.

## Communicative Outcomes of AI-Supported Cross-Cultural Translation

The comparison of survey responses from both the pre- and post- stages of the intervention determined the effectiveness of the communication process. Overall, there was an improvement in information clarity of 26% among participants in the experimental setting, as reported by instructors in the group, compared to a 7% increase in the other group, while the occurrence of unclear moments declined by 19% in the experimental group, and only by 6% in the comparison group. As shown in the table, students expressed generally positive views about the quality of the communication process.

Table 1: Multilingual Students' Perceptions of AI-Supported Translated Communications

| Statement | Agree (%) | Neutral (%) | Disagree (%) |
|---|---|---|---|
| Messages I received felt clear and easy to understand | 80 | 13 | 7 |
| The tone of translated messages felt appropriate and respectful | 77 | 15 | 8 |
| Translated communications felt culturally considerate | 78 | 14 | 8 |
| Translations fully captured the instructor's original intent | 58 | 26 | 16 |
| I would recommend this system for cross-cultural communication | 81 | 12 | 7 |

Table 1 presents respondents' perceptions of messages transmitted via AI-supported translation among multilingual students. The majority of participants expressed an overall positive attitude towards the clarity and cultural appropriateness of messages conveyed in multilingual format. However, agreement regarding the capability of translated messages to convey meaning and intention held by the instructor was somewhat lower.

Analysis of the records of messages revealed that human reviewers mostly dealt with messages that provided evaluative feedback or included changes in schedules, which were also pointed out by students as requiring optimal word choice. Thematic analysis of interview data shows that educators found the system useful for long-distance communications but stressed the necessity of conducting personal reviews of messages whose emotional content demanded careful selection of words.

## Conclusion And Future Directions

This study examined how artificial intelligence can be purposefully designed to support cross-cultural communication through translation systems that integrate cultural calibration alongside linguistic accuracy, and the findings offer encouraging evidence for this direction. The pilot evaluation showed that instructors using the proposed AI-supported system achieved meaningful gains in self-rated communication clarity and reductions in misunderstanding compared with those using conventional translation tools, while multilingual students reported generally positive perceptions of message tone and cultural appropriateness. The system's four-component architecture, comprising a linguistic translation engine, a cultural-context calibration layer, a human-review interface, and a feedback and refinement loop, proved capable of supporting these improvements while preserving human oversight over sensitive exchanges.

At the same time, the study surfaced considerations that must inform future deployment, including the risk of cultural oversimplification, the variable reliability of automated tone detection across language pairs, and the continued necessity of human judgment for emotionally significant communication. Future research should extend this work through broader language coverage, larger and more culturally diverse participant samples, and longitudinal evaluation of communication outcomes beyond the pilot period. Attention should also be directed toward developing clearer guidelines for when automated calibration is appropriate versus when mandatory human review should apply. Taken together, this study reinforces the view that AI-supported translation systems, when thoughtfully designed around cultural calibration and human oversight rather than linguistic accuracy alone, can meaningfully strengthen cross-cultural communication across educational and institutional settings.

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