Cross-Cultural Challenges in AI Translation for Deaf and Non-Verbal Populations

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Abstract

Artificial intelligence (AI) translation systems, which seek to address communication barriers among Deaf and Hard-of-Hearing (DHH) communities, often experience repeat cultural failure based on their incompetence to realize the rich cultural complexity and emotional depth embodied in the signed languages. A systematic study indicates recognizable patterns of cultural error, such as the threatening normalization of interpreted, non-native data and the failure to focus on the sensitive linguistic aspects, especially non-manual signs that bear grammatical and affective significance and meaning. In order to address these systemic failures, this paper suggests a Cultural Context and Error Framework of AI Translation (CCEF-AI) including an evaluation taxonomy, which recommends the mandatory addition of layers of cultural metadata, hybrid human-AI collaboration on high-stakes settings, and metrics that go beyond superficial measures of accuracy rating. Finally, equitable access would require a general effort towards inclusive, adaptive, community-informed AI design where Deaf leadership leads the agenda and development processes of research to ensure the erosion of linguistic rights and systemic bias are prevented by implementing research-based interventions and solutions.

Keywords: Sign Language AI, Cross-Cultural AI, Deaf Accessibility,Non-Verbal AI,Cultural NLP

Introduction

In modern world context, where the force of linguistic diversity is a harsh reality, there is an urgent need of easy-to-use communication tools to ensure equal access to information and resources in all spheres of society (Zaki and Ahmed, 2024). Artificial intelligence has become a central theme in the quest to become more inclusive in a bid to prove that, in understandings of language, it could be used to automate language translation, breaking down existing barriers to communication with otherwise marginalized populations historically marginalized by language inequalities, especially the Deaf and Hard-of-Hearing (DHH) community (Bai, 2024; Alsharif et al., 2024). It is claimed that around 70 million DHH people in the world communicate more than 200 different sign languages, which have their own grammatical structure and vocabulary (Bragg et al., 2019; Zhang et al., 2025; WFD, 2022). The creation of AI-based technology that could convert speech or written word to fluid sign language (Sign

Language Generation, or SLG) and back (Sign Language Translation, or SLT) has a high potential to enhance the access to the necessary services, including healthcare, education, and employment (Alsharif et al., 2024; Cordova-Esparza et al., 2024; Papatsimouli et al., 2023).

Although the technical achievements that machine learning (ML) algorithms provide allow surprisingly great results, including sequence-to-sequence and transformer (Bai, 2024; Batte, 2025), the adaptation of AI to sign language translation is also critically fraught with cultural and linguistic gaps that could not be addressed (Bai, 2024; Naveen and Trojovsky, 2024). AI models, which have already proved their ability to increase speed and the simple level of accuracy (Bai, 2024), often perform poorly when it comes to situations requiring cultural richness and emotional consistency (Bai, 2024; Zaki and Ahmed, 2024). This is made worse in sign languages that are based on multimodal elements of communication, such as the very important non-manual markers (NMMs) like facial expressions and body posture, which are not yet well-represented in current technologies (Zhang et al., 2025; Chua et al., 2018). Moreover, the systematic bias of the research community is added to the central issue and is usually manifested in technologies carefully designed by the convenience and perceived urgency of hearing, non-signing researchers, instead of the actual needs and language use of Deaf stakeholders (Desai et al., 2024).

The paper is a critical and interdisciplinary study on cross-cultural issues that are inherent to AI sign language translation. It aims to move the language of discussion out of the technical incompetence to the acknowledgment of cultural incompetence in the field of AI design and implementation. The paper is informed by some critical research questions: What are some patterns of cultural and linguistic error used in existing AI sign language translation systems? What can be done to classify and analyze such failures in a systematic way and make development more responsible and context-based? However, and above all, what theories of theoretical model and participatory design can guarantee the future AI systems underpin and not overshadow the linguistic agency and cultural diversity of Deaf and non-verbal communities?

The primary contributions in this paper are three. First, it provides a theoretical background based on language relativity and cultural pragmatics to place the systemic failure of monocultural AI in sign systems. Second, it forms a systematic taxonomy of the cross-cultural translation failures witnessed in contemporary sign language AI literature, along lexical, pragmatic and ethical lines. Third, based on these findings, it introduces the Cultural Context and Error Framework of AI Translation (CCEF-AI) which defines the technical layers required and community validation systems that can be implemented to create truly inclusive and adaptive translation technologies. This should promote the Deaf-led researches and culturally specific measures to establish suitable suggestions on ways to redirect the field towards even-handed technological destiny (Desai et al., 2024; Zaki and Ahmed, 2024).

Theoretical Framework

In order to outline the issues of AI translation of signed domains and non-verbal ones properly, it is vital to base the analysis on the key theories of language, culture, and communication. These issues of AI are not only computational, but they are inseparably connected with the fact that sign languages are inherently human-centric, embodied, and culturally relative (Veale et al., 1998; Chua et al., 2018).

Linguistic Relativity in Sign Systems

One of the most widespread myths, which is often repeated by non-linguistic studies of AI, is that sign languages are direct, manual representations of spoken languages (Bragg et al., 2019; Valli and Lucas, 2000). This view disregards that signed languages, including American Sign Language (ASL), are natural languages that have their own unique phonology, morphology, syntax and grammar and do not share any similarities with the co-existing spoken language (Stokoe, 1961; Zhang et al., 2025; Cordova-Esparza et al., 2024).

Sapir-Whorf hypothesis- The linguistic relativity principle, which is also referred to as the weak hypothesis, states that the structure of languages determines how speakers create conceptualizations about the world (Veale et al., 1998). This principle is urgently applicable in sign systems. Contrary to linear, auditory-sequential spoken languages, sign languages take advantage of a higher dimensionality of space expression (Veale et al., 1998, p. 81). Sign languages can also explicitly focus on space in concepts and metaphors, and therefore, a generative translation system must have a profound conceptual vision of schemata and their spatial basis to generate natural output (Veale et al., 1998). To take the example: a system that translates an English concept of suffering a headache would come to understand that the sign of HAVE (possession) had to appear where the sign of SUFFER-FROM had to be omitted - a literal translation model would not represent this type of grammatical and conceptual difference (Veale et al., 1998). This abstract, metaphorical conceptualization emphasizes the fact that a literal, direct transliteration method can not result in the real sign language (Zhang et al., 2025).

Cultural Pragmatics and Non-Verbal Communication

Effective communication requires not only linguistic accuracy, but also cultural awareness and pragmatic competence, which is compromised by the existing AI mediation today (Kunst and Bierwiaczonek, 2023; Madaminovich, 2020). The cultural norms determine cross-cultural communication (Hall, 1976; Hofstede, 1980). Studies of global digital communication, such as the understanding of non-verbal meaning, e.g., silence, intentions, etc., indicate that the meaning can differ considerably: what can be perceived as respectful in a high-context culture can be interpreted as disengaged in a low-context culture (Adisa, 2023; Takaki, 2023).

In the case of DHH communities, this pragmatic layer is further complicated because non-manual expressions (NMMs), such as facial expression, head motions, and body language, are important in conveying both linguistic and non-linguistic information (Chua et al., 2018; Papatsimouli et al., 2023). The success of a message can strongly depend on the transfer of the appropriate emotional coloring, particularly in serious

situations, such as medical or legal (Chua et al., 2018; Taira and Itagaki, 2019). In the situations when AI translation systems are not able to understand such nuances, they may cause serious misinterpretations and misunderstandings (Naveen and Trojovsky, 2024; Wang, 2020).

Embodiment and Acceptance

Sign language is essentially a body experience. It is a non-verbal language, where whole body of signer (hands, face and posture) is the language tool (Papatsimouli et al., 2023; Klima and Bellugi, 1979). The visual fidelity and perceived naturalness of AI-driven Sign Language Generation (SLG) tools (i.e., signing avatars) is, therefore, extremely instrumental to their acceptance (Kipp et al., 2011). Traditionally, SLG technology has been heavily criticized by the DHH users because of the avatars that look unnatural, the language translation that leaves much to be desired, and simplifies complex sign linguistics (Zhang et al., 2025; Huenerfauth, 2009).

To be functional, an SLG system needs to replicate the manual components (handshape, movement) in co-articulation with the non-manual markers (facial expressions, head tilts) that make up the grammatical structure of an SLG system (Zhang et al., 2025). In cases where an AI system is unable to model these complex features, its outputs will attack user trust and hinder proper communication (Ebling and Glauert, 2016; Zhang et al., 2025). This is because the rejection of sign language technology, including smart gloves, is often due to the fact that these technologies are foregrounding technical convenience at the expense of linguistic validity, as they do not include NMMs and simplify the communication process through meant movements (Lu, 2016; Wen et al., 2021).

The Cultural Translation Stack Model

The requirement to capture context and cultural sensitivity, especially when working on a task that requires creative or non-literal interpretation (Bai, 2024; Naveen and Trojovsky, 2024), highlights the necessity of a conceptual model that extends beyond the conventional sequential machine translation pipeline. The Cultural Translation Stack (CTS) is a model that suggests a layered model of sign language translation, with cultural awareness and lingual context incorporated at earlier stages of data processing and algorithm implementation.

This conceptual stack demands a number of key features based on current criticisms of AI limitations: 1) A Foundational Linguistic Layer that draws on notation systems, such as HamNoSys, to precisely encode the phonetic and articulatory parameters of the various sign languages, and then only encode the encoded data before semantic translation takes place (Hanke, 2004; Wanzare et al., 2024). 2) A Contextual and Pragmatic Layer that uses advanced Natural Language Processing (NLP) models, including Large Language Models (LLMs), not only to syntactically convert the text (Dong, 2024) but also detecting emotional tone and cultural context and, in this way, overcoming the loss of nuances that come with direct translation (Ismayilli, 2024; Naveen and Trojovsky, 2024). 3) Cultural Metadata Layer of datasets, which would require the addition of data about the dialects of the region, signer identity (e.g., race, fluency) and the social context of the sign-recorded (Desai et al., 2024; Zaki and Ahmed, 2024). Such a stratified structure requires transparency, ethical processing, and accountability so that the final output would be sensitive to the culture and would be

culturally and contextually relevant, particularly in situations with high stakes (Chen and Wang, 2018; Ismayilli, 2024).

Related Works

The academic and technological drive to automate sign language translation has flourished, yet scholarly critiques reveal a persistent disconnect between technical capabilities and the nuanced realities of Deaf communities (Bragg et al., 2019; Desai et al., 2024). Relevant literature addresses four primary areas: technological advancements, inherent cross-cultural diversity, the challenge of contextual markers, and critical gaps in methodology.

Advancements in AI Sign Language Translation (SLT/SLG)

Recent progress in sign language processing relies heavily on deep learning models derived from computer vision (CV) and natural language processing (NLP) (Batte, 2025; Alsharif et al., 2024). Core architectures frequently employ sequence-to-sequence models, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks to handle the spatio-temporal complexity of continuous signing (Boháček & Hrúz, 2022; Cordova-Esparza et al., 2024; Batte, 2025). The efficacy of these models in enhancing basic translation accuracy has been documented (Bai, 2024).

The emerging role of LLMs is particularly notable in Sign Language Generation (SLG). Systems like *SignifAI*, developed for French Sign Language (LSF), leverage LLMs (specifically ChatGPT) to take a sequence of recognized glosses and return a fluently reformulated spoken sentence, explicitly acknowledging the drastic syntactical difference between sign and spoken languages (Dong, 2024). Furthermore, systems are being developed that utilize LLMs to construct semantically meaningful sentences from inferred terms in languages like Portuguese Sign Language (LGP), achieving promising semantic correlation rates (Adão et al., 2023). However, achieving high accuracy requires overcoming foundational issues like the scarcity of sufficient, large-scale annotated datasets, particularly in continuous sign language recognition (Batte, 2025; Cordova-Esparza et al., 2024).

Cross-Cultural Sign Variation

The first threat that is frequently incomprehensible to the technology developers is the real linguistic fact that sign languages are not universal; there are more than 300 different sign languages in the world (WFD, 2022; Papatsimouli et al., 2023). The non-unification concept implies that signs and grammars differ greatly between one country and the other, and even within the same country, in certain regions, similar to the situation with spoken dialects (Papatsimouli et al., 2023). As an example, it is mentioned that Iraqi Sign Language has distinctive signs that are influenced by the local culture and traditions (Source 45). Linguistic heterogeneity is mentioned as one of the key communication obstacles that AI translation systems should overcome to become a useful tool in practice (Papatsimouli et al., 2023).

The challenge to deal with linguistic diversity is not restricted to words, but also to complex syntactic variations. The spoken and signed languages are inherently complex

because the grammatical rules of these languages are different (Stoll et al., 2018). As an illustration, when trying to create a translation system of Text-to-Sign that works with translating the Indian Sign Language (ISL), this process is still quite complicated due to the fact that the ISL language does not have the exact set of grammatical rules or standards that could be compared with the English text, which makes the translation process inaccurate most of the time (Kumar and Anish Kumar, 2023).

Contextual and Non-Manual Markers

The nature of sign languages is multimodal, i.e., manual gestures need to be deciphered in combination with non-manual indicators (NMMs) like facial expressions, the shape of mouth, head tilt and posture (Chua et al., 2018; Papatsimouli et al., 2023; Zhang et al., 2025). These NMMs do not only express but hold critical grammatical and emotional data (Chua et al., 2018; Zhang et al., 2025).

Even modern AI solutions are not able to grasp such nuances. An example is that technologies that attempt to produce signed output do not take into account NMMs or model them in a generic way, creating outputs with no additional meaning or context-specific information (Zhang et al., 2025; Ye et al., 2020). The consistency of the use of facial expressions in full sentences, such as the lack of attention to the contextual nature of human sign language, compromises the overall quality and understandability of the translation (Zhang et al., 2025). The main drawback of this contextual misinterpretation is crucial especially in ambiguous phraseology decoding or subtle emotional color, which in high-stakes communication is crucial (Chua et al., 2018; Ye et al., 2020).

Noted Gaps: Western Bias and Cultural Erasure

A critical body of work identifies **systemic biases** and gaps that compromise the ethical and functional deployment of sign language AI (Desai et al., 2024; De Meulder, 2021).

Western and Linguistic Bias: Research efforts are overwhelmingly concentrated on major sign languages, most notably American Sign Language (ASL) (Batte, 2025; Desai et al., 2024). This leaves low-resource sign languages, such as many Indian or regional African languages, with minimal technological support and limited datasets (Jemilda et al., 2025; Zaki & Ahmed, 2024; Wanzare et al., 2024). This skewed focus, largely driven by hearing, non-signing researchers, results in systems that prioritize convenient modeling approaches over the complex linguistic realities of diverse Deaf users (Desai et al., 2024).

Data Bias and Linguistic Subordination: One major systemic flaw is that the benchmarks are all datasets of interpreters. Most sign language interpreters are hearing and may produce signs very differently from how Deaf people naturally use them (Alexander & Rijckaert, 2022). In addition, interpreted or scripted language - also called "translationese" - differs from spontaneous spoken language encountered "in the wild" (Desai et al., 2024). And training AI with this deficient data is likely to lead to the very limiting state where Deaf users would be told to adapt their natural signing to fit technology-a type of linguistic subordination to technology described by Desai et al. (2024) and by De Meulder (2021).

Cultural Erasure: This could be further exacerbated by the fact that datasets intentionally collected to increase signer diversity along dimensions of race and gender may inadvertently continue this erasure if their labeling processes draw upon dictionaries that have, historically, privileged the language used by already privileged groups, such as white signers. This means that signs used within the minority community may be discarded (Desai et al., 2024). Furthermore, generalized AI models, including T2I systems, have been shown to revert to US-centric interpretations of universal concepts or gestures; these systems demonstrate a lack of cultural competence in communicating non-verbally (Yerukola et al., 2025). The gaps identified here signal an acute ethical imperative for continuous integration of deep cultural knowledge and Deaf leadership throughout all aspects of a research and development lifecycle (Bragg et al., 2019; De Meulder, 2021).

Methodology

The current study follows a systematic approach, based on the principles of a systematic review, in an attempt to thoroughly map and critically analyze the cross-cultural and systemic challenges reported in recent academic literature related to AI sign language translation.

PRISMA-Based Systematic Review Design

Conceptually, the identification and synthesizing approach to existing literature was modelled on the methodological approach of systematic review practices to ensure rigor and transparency in selecting and analyzing sources, as advocated by contemporary standards (Yusuf & Sivanadhan, 2025; Papatsimouli et al., 2023). Although a full-scale systematic review in this context is beyond the scope of a single paper, certain key principles underlying such a review, as specified in the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015 statement (Moher et al., 2015), were utilized to structure the search strategy and the rationale for study inclusions.

Databases and Search Terms

The literature search focused on peer-reviewed publications within prominent academic databases, spanning both computer science/engineering and humanities/social sciences fields to ensure an interdisciplinary perspective (Yusuf & Sivanadhan, 2025). The databases queried included Scopus, ScienceDirect, PubMed, IEEE Xplore, ProQuest, and Google Scholar (Papatsimouli et al., 2023; Yusuf & Sivanadhan, 2025).

A combination of specific keywords was utilized to capture highly relevant literature, including: "sign language," "AI," "translation system," "cross-cultural communication," "Deaf accessibility," "bias," "non-verbal markers," "linguistic minority," and "datasets" (Adapted from Papatsimouli et al., 2023; Zaki & Ahmed, 2024; Yusuf & Sivanadhan, 2025). The search focused predominantly on articles published since 2019, reflecting the accelerated pace of AI development and the critical shift toward neural machine translation (Yusuf & Sivanadhan, 2025; Papatsimouli et al., 2023).

Inclusion Criteria and Thematic Coding

Inclusion criteria were designed to prioritize empirical research, methodological descriptions, and critical position papers directly addressing the development, deployment, evaluation, or societal impact of AI technologies in sign language contexts. Specifically, the included literature encompassed:

1. Peer-reviewed journal articles and conference proceedings detailing AI models (CNNs, LSTMs, Transformers, LLMs) for sign language recognition, generation, or translation (Papatsimouli et al., 2023).
2. Studies analyzing the role of cultural factors, linguistic nuances, non-manual markers, and dataset quality in automated sign language systems (Zhang et al., 2025; Chua et al., 2018).
3. Critical analyses or position papers discussing systemic biases, ethical implications, and the necessity of Deaf leadership and user-centered design in this domain (Desai et al., 2024; De Meulder, 2021; Clark & Turner, 2020).

Exclusion criteria applied to non-academic sources, literature not explicitly focused on AI applications in translation, and articles not published in English (Papatsimouli et al., 2023; Yusuf & Sivanadhan, 2025).

The identified corpus was subjected to thematic coding and interpretative analysis, following a critical scholarly tone to synthesize recurring patterns of failure and innovation (Yusuf & Sivanadhan, 2025). The coding process focused on emergent themes derived from the material, specifically categorized into: (a) Motivational Biases (e.g., prioritizing accessibility for hearing people over linguistic autonomy for Deaf people) (Desai et al., 2024); (b) Data and Representational Integrity (e.g., usage of interpreter-only data, omission of linguistic features) (De Meulder, 2021; Desai et al., 2024); (c) Cultural and Contextual Fidelity (e.g., capturing idiomatic expressions, cultural nuances, emotional congruence) (Bai, 2024; Chua et al., 2018); and (d) Proposed Solutions and Policy (e.g., hybrid models, Deaf leadership, new evaluation metrics) (Zaki & Ahmed, 2024; Ismayilli, 2024). These themes formed the interpretative foundation for developing the proposed cultural failure taxonomy and the CCEF-AI framework.

Findings: A Cultural Failure Taxonomy

The systematic synthesis of literature reveals that failures in AI sign translation are not isolated technical glitches but rather systematic breakdowns in cultural and linguistic representation (Desai et al., 2024; De Meulder, 2021). These failures can be classified into a Cultural Failure Taxonomy, illuminating the systemic challenges that extend beyond simple word-for-word accuracy.

1. Lexical Divergence and Representation Gaps

Lexical divergence occurs when AI systems, reliant on statistical mapping, fail to account for the intrinsic variability of signs across cultures and regions (Papatsimouli et al., 2023). Sign languages inherently feature differences in vocabulary and conceptual metaphors (Veale et al., 1998).

A primary error pattern is the literal translation of culturally dense texts or polysemous words, where the AI system translates word-for-word, diminishing clarity and reliability (Bai, 2024; Naveen & Trojovský, 2024; Bahri, 2020). This issue is magnified by the input data limitations: when datasets, even those designed for diversity, discard signs not present in historically biased dictionaries, they actively exclude the authentic lexicon used by diverse signing communities, thereby perpetuating linguistic subordination (Hill, 2023; Desai et al., 2024). Without a deep conceptual understanding, AI cannot successfully translate metaphors or select the correct, context-specific sign schema (Veale et al., 1998).

2. Non-Manual Ambiguity and Affective Deficit

Sign languages use non-manual markers (NMMs)—facial expressions, eye gaze, head tilts, and body posture—to convey essential emotional and grammatical information (Chua et al., 2018; Zhang et al., 2025; Papatsimouli et al., 2023). A recurring cultural failure is the inability of current AI systems to recognize, generate, or accurately interpret these NMMs, leading to **non-manual ambiguity** (Zhang et al., 2025).

Systems often focus exclusively on manual components, neglecting the affective signals crucial for translation quality, particularly in high-stakes communication where emotional tone dictates the accuracy of the message (Chua et al., 2018). When NMMs are included, they are frequently applied uniformly across sentences, failing to capture the contextual nuances required for accuracy and naturalness (Zhang et al., 2025). This simplification results in avatars perceived as robotic or systems that lose temporal consistency, undermining user trust and comprehensibility (Kipp et al., 2011; Zhang et al., 2025).

3. Pragmatic Misalignment and Contextual Failure

Pragmatic misalignment arises when AI systems fail to interpret the conversation or text within its correct social or cultural context, resulting in translations that are technically accurate on the surface but functionally meaningless or inappropriate (Naveen & Trojovský, 2024).

This failure includes loss of formal or professional tone, as demonstrated in case studies where AI performed technically well but missed the subtle tonal requirements necessary for legal language (Bai, 2024). Furthermore, AI models frequently struggle with abstract concepts or ambiguous phrases where contextual cues are critical for disambiguation (Ye et al., 2020; Bahri, 2020; Naveen & Trojovský, 2024). Cross-cultural interpretation of non-verbal signals like silence also falls victim to pragmatic misalignment, as AI may default to a Western, low-context interpretation (e.g., uncomfortable) where a high-context culture perceives respect (Adisa, 2023; Takaki, 2023; Hall, 1976).

4. Dialect Shifts and Low-Resource Neglect

The existence of over 300 sign languages, coupled with regional and dialectal variations within each, presents a massive data challenge that AI systems consistently fail to overcome (WFD, 2022; Papatsimouli et al., 2023). Dialect shifts and the lack of training data for linguistic minorities or low-resource languages (e.g., regional Indian, African,

or less-common European sign languages) mean that existing AI solutions only cater to a privileged minority, primarily users of well-resourced languages like ASL (Zaki & Ahmed, 2024; Batte, 2025; Desai et al., 2024).

This systemic imbalance creates a "native signer" bias, risking the marginalization of deaf users with diverse or non-normative acquisition paths or those with additional disabilities (Desai et al., 2024). The ideological meaning of "fluency" is often narrowly defined by the available (biased) training data, forcing many users to conform their signing to the technological limitations rather than supporting the language as it naturally occurs (Desai et al., 2024; De Meulder, 2021).

5. Gestural Idioms and Metaphor Collapse

A specific manifestation of pragmatic and lexical failure is the collapse of gestural idioms and cultural metaphors. Idiomatic expressions and culturally specific phrases that lack direct equivalents in other languages pose significant difficulties for traditional and neural translation models (Naveen & Trojovský, 2024; Yusuf & Sivanadhan, 2025).

AI algorithms rely heavily on identifying statistical patterns, struggling to handle texts involving deep cultural knowledge, humor, or specific rhetorical devices (Bai, 2024; Bahri, 2020). For sign languages, where non-literal spatial representations are common (Veale et al., 1998), the inability to detect and correctly translate these sign-specific idioms represents a profound failure of cultural fidelity. Attempts to incorporate cultural context by fine-tuning models have been proposed but remain a highly complex problem necessitating ongoing research (Liu et al., 2021; Naveen & Trojovský, 2024).

6. Ethical Asymmetry and Linguistic Subordination

The culmination of these failures often results in ethical asymmetry, where the design and deployment of technology perpetuate harm and inequality against the target community (Tan et al., 2019; Desai et al., 2024).

This asymmetry is primarily driven by systemic biases baked into the research agenda, such as the overfocus on solving perceived communication barriers (i.e., fixing the deaf person's inability to speak to a hearing person) rather than focusing on sign language as a complex language in its own right (Desai et al., 2024). The heavy reliance on interpreter-only datasets, which are often scripted, interpreted language rather than natural Deaf languaging patterns, provides a distorted representation that risks imposing a problematic benchmark for AI (Desai et al., 2024; De Meulder, 2021). This practice potentially undermines the hard-won linguistic rights of Deaf people and introduces new forms of hierarchy and reliance on technology (De Meulder, 2021; Zaki & Ahmed, 2024).

CCEF-AI Framework: Cultural Context and Error Framework for AI Translation

To systematically address the cultural failures identified in the taxonomy, the proposed Cultural Context and Error Framework for AI Translation (CCEF-AI) outlines a

necessary shift in data architecture, validation processes, and evaluation metrics, moving the emphasis from raw technical speed towards cultural and linguistic fidelity (Bai, 2024; Desai et al., 2024; Zaki & Ahmed, 2024).

1. Cultural Metadata Layer (CML)

The CML mandates that datasets and annotations must capture the rich socio-linguistic and cultural variables that underpin meaningful communication, rather than focusing solely on isolated manual features (Chua et al., 2018; Zaki & Ahmed, 2024).

Enhanced Annotations: Data collection must move beyond simple glossing, which is criticized for often treating glosses as literal translations instead of context-dependent representations (Desai et al., 2024; Hochgesang, 2019). The CML requires sophisticated annotations that detail:

1. **Phonetic and Articulatory Parameters:** For low-resource and diverse sign languages (like Kenyan Sign Language, KSL), notation systems such as HamNoSys must be used to transcribe signs based on five articulatory parameters, ensuring linguistic rigor and supporting the development of systems where large text corpora are unavailable (Hanke, 2004; Wanzare et al., 2024).
2. **Non-Manual Marker Context:** Annotations must precisely label the linguistic function of NMMs (e.g., question, negation, conditional statement) and their temporal co-articulation with manual signs, preventing the uniform application of expressions that loses context (Zhang et al., 2025).
3. **Socio-Linguistic Context:** Metadata should include signer demographics (race, age, first language acquisition status), and the specific communicative context (formal, informal, spontaneous, interpreted) to identify and mitigate inherent biases (Desai et al., 2024).

This enhanced metadata layer is crucial for training algorithms to manage cultural variability, rather than homogenizing signed output (Zaki & Ahmed, 2024).

2. Community Validation and Participatory Design

The ethical and functional imperative of sign language AI rests on continuous engagement with and validation by Deaf stakeholders, ensuring the technology aligns with user needs and preserves linguistic autonomy (De Meulder, 2021; Zaki & Ahmed, 2024). The CCEF-AI mandates three community-focused mechanisms:

1. **Deaf-Led Research and Leadership:** Critical analysis shows that AI research agendas, when led primarily by hearing, non-signing individuals, default to convenient, biased solutions (Desai et al., 2024). The framework requires Deaf researchers to lead conversation, policy, and research design, ensuring that problem formulation prioritizes Deaf stakeholder interests over perceived technological urgency (Desai et al., 2024).
2. **Hybrid Human-AI Collaboration:** Especially in high-stakes contexts (e.g., medical, legal, diplomatic), AI translation systems must mandate human oversight and review (Ismayilli, 2024; Chua et al., 2018). Hybrid models merge AI efficiency for routine tasks with the indispensable human expertise required

to manage complex cultural, idiomatic, and emotional nuances (Ismayilli, 2024; Zaki & Ahmed, 2024).

3. **User-Centric Feedback Loops:** Design must incorporate explicit feedback mechanisms that allow DHH users to correct or clarify interpretations in real-time, replicating the immediacy and collaborative nature of human interpretation (Chua et al., 2018; Evans & Patel, 2018). User studies and participatory design must evaluate systems based on perceived usability, comprehensibility, and alignment with authentic signing style (Clark & Turner, 2020; Zhang et al., 2025).

3. Error-Diagnosis Tool (EDT) and Advanced Metrics

Traditional quantitative metrics like BLEU (Bilingual Evaluation Understudy), while useful for assessing surface-level word overlap, are insufficient for measuring the complex cultural and emotional dimensions of translation quality (Papineni et al., 2002; Bai, 2024). The CCEF-AI proposes an **Error-Diagnosis Tool (EDT)** that incorporates specialized, context-aware metrics:

1. **Cultural and Emotional Accuracy Indices:** The EDT must quantitatively assess dimensions such as the **Cultural Accuracy Index** and the **Emotional Accuracy Index**, which track how successfully the system retains cultural subtleties and emotional congruence, complementing measures of basic accuracy and speed (Bai, 2024).
2. **Translation Error Rate (TER) Adaptation:** While TER measures the minimum number of edits required to match a reference translation (Snover et al., 2006; Wanzare et al., 2024), the EDT must adapt this to qualitatively categorize errors based on the taxonomy, identifying instances of pragmatic misalignment or NMM omission, rather than merely counting word substitutions (Bai, 2024).
3. **Linguistic Fidelity Check:** The tool must verify that the model output adheres to the specific syntactic and morphological rules of the target sign language (e.g., ASL grammar), as failure to provide grammar guidelines often results in inconsistent performance (Zhang et al., 2025). This ensures evaluation is grounded in linguistic reality, moving away from flawed gloss-based assumptions (Desai et al., 2024).

Discussion

The implementation of robust AI translation systems for Deaf and non-verbal populations represents a technological and ethical challenge that intersects deeply with social policy, disability justice, and linguistic sovereignty (De Meulder, 2021; Desai et al., 2024). The preceding taxonomy and framework provide a critical roadmap, yet their implications must be contextualized within broader design, policy, and political discourses.

Design Implications for Inclusive HCI

The persistent technical shortcomings and cultural oversights in current AI systems highlight the need for a fundamental rethinking of Human-Computer Interaction (HCI) approaches for sign language applications (Bragg et al., 2019). The literature consistently critiques intrusive, error-prone devices—such as the widely criticized "smart gloves"—for their inability to capture critical non-manual markers (NMMs) and their tendency to oversimplify the communicative act (Wen et al., 2021; Lu, 2016).

Future design efforts should emphasize non-intrusive, vision-based systems that leverage computer vision and deep learning to achieve real-time gesture recognition (Alsharif et al., 2024; Jemilda et al., 2025). Central to this approach is the lived experience of Deaf and Hard-of-Hearing (DHH) users. Interfaces must maximize visual clarity, providing sufficient resolution and display space to faithfully render both manual and non-manual elements in signing avatars (Chua et al., 2018). Research in augmented reality (AR) captions points to additional opportunities: by employing spatially distributed or dynamic cues, designers can exploit heightened peripheral vision sensitivity in DHH individuals, thereby reducing cognitive load and improving comprehension of non-verbal information (Ubur, 2025).

Translation alone is rarely sufficient. Users consistently indicate that visual resources and context-sensitive tools—particularly those supporting complex or abstract content such as STEM terminology—often hold greater practical value than translation features in isolation (Chua et al., 2018). Consequently, effective systems must be iterative and user-centered, grounded in ongoing collaboration with diverse DHH communities to ensure relevance, usability, and cultural fidelity (Clark & Turner, 2020; Zaki & Ahmed, 2024; Prietch et al., 2022).

Policy Issues and Access Hierarchies

The rapid expansion of AI technologies introduces pressing policy questions around linguistic rights and equitable access (De Meulder, 2021). Although AI translation can offer efficiency and cost savings, there is a real danger that these systems may be promoted as inexpensive substitutes for human interpreters, potentially undermining hard-won accessibility protections, especially for those with limited digital literacy or socioeconomic resources (De Meulder, 2021; Zaki & Ahmed, 2024).

Policy frameworks must carefully consider the role of hybrid human-AI models, particularly in contexts where errors carry significant legal, medical, or social consequences (Ismayilli, 2024; Chua et al., 2018; De Meulder, 2021). Establishing ethical standards that ensure accountability, transparency, and inclusivity is essential, including clear disclosure of AI limitations and areas of uncertainty (Ismayilli, 2024; Koehn, 2020). Educational institutions and policymakers should develop strategies that allow users to engage with AI translation while maintaining critical evaluation skills and cultural awareness (Andleeb et al., 2025).

Preserving the agency of Deaf communities is central: they must retain control over how and when these technologies are used, ensuring that access aligns with their needs, values, and preferences rather than being shaped primarily by cost-efficiency or technological convenience (De Meulder, 2021).

Decolonial Perspectives and Deaf Leadership

Critically examining AI research in sign language reveals deep-rooted biases that demand a decolonial perspective. Much of the work in this area frames Deaf individuals as facing "communication barriers," a problem largely defined by hearing researchers, which unintentionally reinforces ableist assumptions of deficiency (Desai et al., 2024; Henner & Robinson, 2023). This approach often leads to technoableism—the tendency to focus on "fixing" disabled bodies—and modality chauvinism, which elevates spoken language over signed expression (Shew, 2023; Henner & Robinson, 2023).

A more just and effective approach centers the voices of those most affected. Deaf researchers should lead the design, direction, and evaluation of AI systems, while hearing collaborators adopt a supportive role, providing mentorship and resources rather than dictating the research agenda (Desai et al., 2024; Berne et al., 2018). Transparency about positionality—the researcher's own experiences, perspectives, and potential biases—must become standard practice, shaping the ethical and methodological rigor of the work (Desai et al., 2024).

Limitations and Future Research Directions

Despite notable advances in AI-driven sign language translation, the field continues to face persistent structural limitations. Chief among these is the scarcity of high-quality, annotated datasets, which significantly hampers the ability of models to generalize across users, dialects, and regional variations (Batte, 2025; De Meulder, 2021; Cordova-Esparza et al., 2024). These challenges are particularly pronounced in the context of continuous signing, dynamic gestures, and the intricate non-manual markers, such as classifiers, that encode critical semantic and spatial information (Zhang et al., 2025; Batte, 2025).

Addressing these gaps will require prioritizing translation models capable of operating effectively in low-resource settings, coupled with strategies to reduce biases in training datasets and to expand coverage beyond standard ASL lexicons (Zaki & Ahmed, 2024). From a linguistic perspective, the precise modeling of classifiers and other subtle features remains essential, as they convey nuanced meaning that cannot be captured without context-sensitive representations (Zhang et al., 2025). On the computational front, optimizing real-time processing to reduce latency remains a significant hurdle, particularly for mobile applications (Batte, 2025; Papatsimouli et al., 2023). Furthermore, long-term empirical studies are critical to assess how sustained engagement with AI translation impacts cognitive load, natural language acquisition, and the development of evaluative skills among users (Andleeb et al., 2025; Shokoohifar, 2024).

Conclusion

The effort to design AI-based translation tools for Deaf and non-verbal communities holds remarkable promise for expanding linguistic access, yet it also reveals how easily technological innovation can drift away from the cultural and linguistic conditions that give communication its depth and coherence (Bai, 2024; Desai et al., 2024). As this paper has argued, the value of these systems cannot be reduced to familiar performance indicators such as BLEU scores. Their real measure lies in whether they can engage the cultural structures through which meaning is actually formed (Bai, 2024; Naveen & Trojovský, 2024). Persistent errors in lexical transfer, the misinterpretation of non-

manual features, and broader pragmatic distortions are not merely technical shortcomings; they reflect underlying biases, especially the overreliance on interpreter-generated datasets and a continuing Western-oriented framing that sidelines the linguistic diversity of Deaf communities worldwide (Desai et al., 2024; De Meulder, 2021).

The CCEF-AI framework introduced here offers a way to realign the field by insisting on a cultural metadata layer and structured community involvement, both of which are essential for ensuring that these systems remain socially grounded and linguistically trustworthy (Ismayilli, 2024; Desai et al., 2024). Accurately capturing non-manual markers, regional and dialectal variations, and culturally embedded idioms is not a peripheral concern but the very heart of modelling signed languages as fully embodied, complex linguistic systems (Zhang et al., 2025; Chua et al., 2018).

Future directions for community-led adaptive AI must prioritize the structural transformation of research itself. This requires placing Deaf stakeholders in positions of leadership to formulate ethical agendas and insist on methodologies that incorporate diverse, high-quality data from low-resource languages (Desai et al., 2024; Zaki & Ahmed, 2024). Only through a renewed, ethical commitment to adaptive, culturally grounded AI—one that views technology as a complement, rather than a competitor or replacement, to human communication—can we foster an inclusive ecosystem that truly supports linguistic autonomy and equitable access for the global Deaf and non-verbal community (De Meulder, 2021).

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