ASL Educators' Perspectives on AI for Enhancing Student Learning in American Sign Language Education

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Abstract

Interest in learning American Sign Language (ASL) is growing across higher education institutions in North America, as reflected in rising enrollments. Yet this growth is constrained by limited program availability and few opportunities to practice outside the classroom. AI-based technologies show promise for supporting ASL learning, but educators – who bring essential pedagogical, linguistic, and cultural expertise – have been largely absent from conversations on the design of these tools, with prior work focusing primarily on learners. To address this, we conducted formative interviews with eleven Deaf and one hearing ASL instructor, followed by two focus groups with six Deaf educators, to examine how AI tools could support ASL education. Findings revealed priorities for technology design and considerations for integration into existing pedagogical practices, with attention to curricular, linguistic, and access factors. We offer insights for designing and researching technologies aimed at (1) providing adaptive, structured feedback on signing performance and (2) supporting immersive conversational practice with virtual signing partners.

CCS Concepts

• **Human-centered computing → Accessibility design and evaluation methods**; *Accessibility technologies.*

Keywords

American Sign Language, ASL, ASL Learning, Sign Language Learners, Deaf and Hard of Hearing, Deaf Culture, Sign Languages, Education, Artificial Intelligence, AI, Perspectives on AI, ASL Educators

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1 Introduction

American Sign Language (ASL) is the primary language for approximately 500,000 people in the US [110], as well as for people in Canada [59]. Many people are motivated to learn ASL, including parents, relatives, caregivers of DHH people, aspiring interpreters, and researchers working with the DHH community [132]. However, ASL is also considered one of the hardest languages to learn [86], thus making guided ASL instruction important for those seeking to develop proficiency. Although fewer than fifty ASL/English interpreting programs exist in U.S. higher education, hundreds of colleges now offer introductory ASL courses [1, 29, 36, 146]. Growing enrollment in ASL and Deaf Studies has made ASL the third most studied language in the U.S. [100, 102].

As demand for ASL education grows, researchers and developers are exploring how artificial intelligence (AI) might support ASL learners. Sign languages have drawn attention from AI and human-computer interaction (HCI) researchers for over four decades, with advancements in sign recognition, generation, translation, and interfaces [24, 57]. These advances have the potential to improve ASL learning [21, 24, 123, 166], but we need to approach this carefully. Researchers have raised concerns about fairness, ethics, and inclusion in AI design for ASL technologies [23], with some work highlighting social and linguistic complexities of ASL and the lack of inclusion of d/Deaf stakeholders [45].

In the broader HCI landscape, prior work shows that educators often conceptualize AI as "human-like," intelligent machines capable of learning from data and solving problems, and although they view AI literacy as important, they frequently lack formal training and specialized tools to teach it [85]. Studies of social perceptions around generative AI (GenAI) in education show that teachers must navigate students' concealed AI use and make sense of non-disclosure [2]. While systems can support adaptable materials, ideation, and personalized feedback, they also raise concerns about authorship, student agency, and bias [62]. Consequently, HCI scholars argue for centering educators in design, highlighting opportunities to mitigate harms through interaction design while recognizing that challenges like institutional power and labor constraints require empowering educators as key actors [63].

Building on these perspectives, a growing body of HCI work focuses on language educators' perceptions of AI tools. Language teachers report that AI applications help tailor tasks to proficiency levels and learning styles (e.g., [33, 48, 58]), and they emphasize involving educators in the design of learner-facing tools for written and spoken languages (e.g., [63, 115, 127, 130]). In assessment, for example, AI grading tools such as CoGrader are seen as acceptable when they complement rather than replace teacher judgment [143]. Similarly, educators pragmatically adapt to GenAI, adjusting assignments and discussing its use with students while expressing concerns about dependency and integrity [157].

Unlike the growing literature on AI for written and spoken language learning, ASL has received limited attention in educator-centered AI design [53, 83, 129]. Prior work has largely focused on ASL learners when developing learning tools [65, 66, 69, 167], with ASL educators—particularly d/Deaf educators—often relegated to peripheral roles such as monitoring studies or assisting with assessments [78]. This gap is especially concerning given ASL's unique learning demands, including spatial reasoning, three-dimensional grammar, and non-manual signals such as facial expressions and body shifts [132, 165], as well as the cultural and affective dimensions of Deaf communication [107, 135]. To effectively support ASL learners, AI tools must be grounded in the experiences, values, and teaching practices of ASL educators.

Therefore, we conducted one of the first studies to examine how ASL educators in U.S. higher education envision the role of AI in supporting ASL learners. Our motivation to focus on higher education was also influenced by our team's experiences working with and/or being higher education educators, and because other non-accessibility AI research has demonstrated the value of focusing on understanding higher education educator needs [164]. We conducted formative interviews with 12 ASL educators and follow-up focus groups with 6 educators to examine (1) *what AI-driven systems or features educators view as most beneficial for ASL learners* and (2) *how AI-based ASL learning tools should align with best practices in ASL pedagogy.*

We contribute empirical insights into ASL educators' perspectives on AI use in ASL teaching, the linguistic and pedagogical considerations that such tools must account for, and the barriers and equity issues that may arise in real-world educational deployment. We also offer design insights for feedback and virtual conversational partners tools. We share how AI can align with ASL instructional practices, such as through moderated, customizable feedback and expressive virtual partners, and offer guidance for designing pedagogically sound and culturally appropriate tools.

2 Background and Related Work

Our work is informed by research on AI in education, ASL pedagogy, and recent AI advancements in ASL learning.

2.1 AI-based Technologies in Higher Education

While higher education offers opportunities for AI integration, educators exhibit varying perceptions. Many educators appreciate AI's potential to enhance learning and ease workloads [32, 64], but expressed concerns about disrupted workflows [8], emotionally detached teaching [169], and student over-reliance and diminished critical skills [41, 87]. Given the varied content across disciplines in higher education, we must complement broader research [105, 111] with work exploring field-specific educators' perspectives.

Higher ed educators could also play a critical role in teaching students to effectively utilize AI tools as supplementary resources [76, 127]. However, many lack formal training in AI use, and pedagogical decisions around AI usage are made without a thorough understanding of the technology's foundations [34, 88]. Therefore, in addition to technology design questions, we need to understand educators' understanding and perception of existing tools.

Like other domains in education [169], research on AI integration in language learning is ongoing [121, 134]. A recent survey of research on AI in higher education settings revealed that most research is on the use of AI for language learning [43]. Emerging studies examine the challenges and strategies for using AI tools in teaching languages [91, 115]. Language educators in prior work have mentioned using AI for lesson planning, class material development, teaching, assessments, and supporting students' independent learning [91, 115]. Educators recognize the need for further critical discussion, guiding policies, and ethical considerations, especially in higher education settings [115].

2.2 Community Perspectives on AI for ASL technologies and Learning Tools

Advancements in AI have spurred efforts to create AI-driven technologies for sign language learning, focusing on delivering more immersive and feedback-oriented learning experiences. AI-driven sign language technologies draw on computer vision techniques originally explored for assistive contexts [21, 23, 67, 166]. These include *sign-recognition* systems for assessment, *translation systems* using animated signing avatars [24, 171], and recently, formative work on the potential of large language models (LLMs) for *sign language generation* [54, 147].

HCI research emphasizes incorporating Deaf perspectives into the design of AI technologies for Deaf users [47, 159] to avoid pitfalls of earlier research technologies, e.g., sign-language gloves [51, 72]. A recent study by Kamikubo et al. [84] found that misconceptions about Deaf people and culture persist even among those actively building ASL AI systems and with prior experience in sign language processing.

Sign language learning tools constitute a distinct design context where users (especially hearing learners not enmeshed in deaf culture) require linguistic, cultural, and pedagogical scaffolding, making Deaf educators' perspectives crucial for ensuring AI aligns with pedagogical reality. While Deaf educators may engage with AI or emerging sign-language technologies in other domains, their views on how AI should support ASL learning are uniquely shaped by instructional goals—much like the differences between perceptions of commercial chatbots, e.g., ChatGPT, and concerns about its use in written-language learning (e.g., [49, 143, 157]).

Sign language learning research has primarily centered on sign recognition technologies, often focusing on word-based recognition [96], as complete sign recognition remains a challenge. Examples include video-based sign language dictionaries [11, 20, 92] and games focusing on vocabulary acquisition [22, 95, 153]. Expressive feedback tools are limited to specific aspects, such as facial expressions [79], though recent work explores additional linguistic feature feedback [70, 123]. AI-powered learning environments have been developed to detect or generate ASL, including AI-based translation systems and gamified VR-based platforms featuring signing avatars [7], and emerging collaborative systems that support non-manual sign learning through shared control of avatars (e.g., CoSignPlay [99]). Additionally, there are some tools to assist ASL educators directly with quizzes or teaching vocabulary [10, 83].

Crucially, most sign language learning technologies research has engaged ASL students as research participants rather than educators [7, 65, 66, 68]. While some studies have included ASL educators in designing comprehension assignments to support student evaluations [78], and formative ethnographic work has explored Auslan language educators' teaching methods and use of early gamified AI-based prototypes [50]. However, aside from a few blogs (e.g., [152, 162]), there remains a notable lack of research that centers Deaf ASL educators as research participants to understand their current usage of chat-based AI systems, preferences for AI-based ASL learning tools, willingness to adopt these tools, and their role in shaping future agendas for AI technologies in ASL education. Since generative sign technologies are still in early stages [24], it is timely to have educators shape these tools before widespread adoption.

2.3 Current Higher Education ASL Pedagogy and Use of Technology

2.3.1 Where is ASL Taught? ASL education and Deaf Studies have grown substantially over the past four decades [126, 132, 165]. ASL is currently the third most studied language at U.S. universities, with over 107,000 enrollments in 2021 [102]. Programs span more than 700 universities and community colleges in the United States [36], the latter enrolling over 30,000 students annually [44]. These programs create pathways for careers in interpreting, linguistics, and related fields [126, 132, 165].

2.3.2 Research on ASL Pedagogy. Scholars characterize ASL pedagogy as fragmented, often relying on "trial-and-error" or intuition rather than established theoretical frameworks or empirical findings [106, 126, 132, 140–142]. Although organizations such as the American Sign Language Teachers Association (ASLTA) offer venues for sharing best practices [39], broader systemic factors shape the landscape. These include the commercialization of ASL courses [28, 138], the widespread use of part-time instructors [39], and curricula grounded more in general linguistic and psychological theories than in ASL-specific pedagogy [140, 156, 158, 165].

Recent scholarship has responded to this gap by examining ASL teaching approaches, instructional tools, curriculum design, and formative and summative assessment practices [93, 150]. While recent scholarship calls for alignment with World-Readiness Standards for Learning Languages[1] [141, 158], adoption is hindered by labor constraints. A focus group with 13 higher education ASL instructors identified both pedagogical and institutional barriers that undermine instructor motivation, particularly among Deaf teachers with advanced degrees [126], while Deaf educators report higher exhaustion than their hearing colleagues because of "cultural taxation"—the burden of serving as linguistic and cultural representatives [98, 138]. This burden is compounded by the intensive grading demands of ASL coursework. Unlike written assignments, video-based work requires close review. Summative assessments such as expressive and receptive tests, quizzes, and video assignments dominate the assessment landscape [30], and instructors report spending roughly 22 minutes per student on tests and 19 minutes on video assignments. Additional studies confirm similar reliance on written exams, expressive presentations, videotaped assignments, and in-class performance tasks [40, 119, 151].

Few empirical studies examine comparative instructional approaches. One recent study comparing inverted and traditional ASL classrooms found comparable performance outcomes, although students in the inverted model reported more opportunities for practice, interaction, and conversational skill building [42]. These insights highlight the value of guided and independent learning environments, which connect to our focus on ASL educators' perspectives on emerging AI tools that may reduce instructional burdens and create new opportunities for practice or feedback.

2.3.3 Diversity and Representation in ASL Pedagogy and Research. Concerns about diversity, representation, and linguistic variation remain widespread across the ASL education literature [30, 98, 126]. For example, scholars have critiqued prescriptive curricula that marginalize natural variation, including Black ASL (BASL) and regional varieties [73]. BASL research shows it to be a systematic and rule-governed dialect with distinctive phonological, morphological, syntactic, and pragmatic features [73, 74]. BASL also preserves older ASL forms and reflects a stronger signing culture rooted in the histories of Black Deaf schools, which experienced different forms of oralist pressure than white Deaf institutions. Yet BASL remains largely absent from mainstream curricula, teacher education programs, and instructional materials, which contributes to linguistic erasure and misrecognition [15, 101]. Similarly, while there is some research on linguistic contact studies, e.g., work on ASL–LSM interactions that documents phonological, prosodic, and syntactic interference [133], their pedagogical implications remain underexplored. These patterns reflect ongoing influences of audism [80] and linguicism [28, 104, 106, 138] on the academic positioning of ASL programs.

[1]https://www.actfl.org/educator-resources/world-readiness-standards-for-learning-languages

Representation among educators mirrors these curricular concerns. Earlier national surveys did not report instructor race or ethnicity [38, 40], and later work shows that 92 percent of instructors in national samples were white [60, 112]. Scholars have emphasized the need to meaningfully expand and support BIPOC representation within ASL teaching [81]. These pedagogical and representational challenges intersect with broader structural conditions in higher education, including the placement of ASL programs outside language departments [126]. Hearing instructors were more likely to report low institutional support, but did not face the cultural and emotional burdens experienced by Deaf faculty.

2.3.4 Use of Technology in ASL Pedagogy. There is some precedence of ASL educators incorporating various technologies in education, including time-synchronized video feedback platforms such as GoReact [1] and TerpTube [71], publicly available feature-based ASL dictionaries [25], commercial curricula such as StartASL, Master ASL!, and The Green Books, and game-based learning tools [22].

Emerging advances in sign-recognition and sign-language technologies introduce new possibilities for ASL instruction. These include recognition of phrases and sentences [3, 160, 168], automated feedback on ASL grammatical constructions [161], sign-language translation [148, 170], and sign-language generation [54]. Although such tools may augment guided or independent learning and address some of the instructional and assessment challenges described above, it remains unclear how educators envision using them, which capabilities they prioritize, and what concerns or constraints shape their interests in AI-based support.

3 Method

We conducted formative interviews with U.S. higher education ASL educators to identify opportunities where AI might support ASL learners and to understand educators' perspectives on designing these technologies. We then conducted two follow-up focus groups where we introduced participants to the state of the art in AI and examples relevant to ideas generated in the interviews (feedback tools and conversational practice partners). The groups discussed how to integrate these technologies into ASL pedagogy. Both studies were IRB-approved.

3.1 Recruitment

We recruited ASL educators teaching at higher educational institutions in the U.S. for our interview study. Our screening recruitment form gathered demographic information, including age, gender, identification as d/Deaf, hard of hearing, or hearing, and prior ASL teaching experience. We distributed the form via academic networks, online platforms (e.g., LinkedIn), the Deaf community, and department chairs at institutions with highly-ranked ASL programs.[2]

Six participants from the interview pool were available for the follow-up focus groups, organized into two groups of three (Group 1: I1, I4, I6; Group 2: I2, I3, I5). Leveraging their prior reflections allowed for deeper insights into AI integration. For clarity in the findings, we use 'F' IDs (e.g., F1, F2) for participant quotes from focus group discussions.

[2]We identified these programs using the U.S. News educational ranking website: https://www.usnews.com/best-colleges/asl-major-1616

3.2 Participants

We recruited 12 ASL educators (nine women, three men)[3] aged 31-67 (mean = 46.8, σ = 11.7). Eleven participants were Deaf educators and one was hearing, with an average of 14 years of teaching experience (among the subgroup who took part in the focus group, all were Deaf). Out of 12 participants, eight shared their racial background: seven participants described themselves as White/Caucasian and one as Black and White biracial. Table 1 includes a breakdown of years of experience, familiarity with sign language AI (SL-AI), and type of institution they are affiliated with.

Most participants primarily taught hearing students, though five occasionally had DHH students. Three participants did not respond to this question. Eight reported teaching students with disclosed and/or visible disabilities, including learning, visual, and mobility impairments. One participant reported no experience teaching students with other disabilities; three did not respond.

3.3 Procedure / Data Collection

We conducted 40-60 minute interviews over Zoom. A senior interpreting student conducted the sessions using a semi-structured interview guide pre-translated into glosses.

The interview guide, refined after four pilot interviews, had three main parts: (1) Questions related to ASL educators' class material to gain an understanding of their teaching routine and current pedagogical resources, (2) Focus on the technologies and tools that educators use for ASL teaching and assignment evaluations, laying the foundation for more detailed questions about AI, and (3) Questions on the potential use cases and limitations of AI and suggestions on responsible AI design. To encourage unconstrained ideation, we withheld specific AI examples initially, only sharing them if participants requested clarification or lacked familiarity. We shared examples of existing AI-based ASL learning tools and current AI capabilities with 5 participants during the study when they asked for further explanation or had not expressed familiarity with any technology before the final part of the interview.

The follow-up focus groups were also conducted over Zoom and lasted 73 and 67 minutes. A Deaf graduate student specializing in HCI facilitated the sessions, with an interpreter assisting with transcription.

We found during our interviews that our participants had varying levels of experience and understanding of AI. Therefore, to enrich the focus group discussions and ground them in the current capabilities and limitations of AI, each session began with a brief Google Slides presentation on AI technologies. We defined AI as "*a method where machines are taught to perceive their environment, learn from it, and choose actions most likely to help achieve a goal.*" [114] The next three slides provided examples to explain the three parts of the definition: "*perceive their environment*," "*learn from it*," and "*choose actions most likely to help achieve a goal*." We then provided examples of use of AI in ASL learning such as immersive environments [7], receptive skills tools [20, 65], expressive feedback systems [68, 78], virtual character usage [55], and AI-driven video generation [54, 149] (see Appendix A for descriptions).

[3]We used gender options provided by the HCI Guidelines for Gender Equity and Inclusivity [144]

Table 1: Demographic characteristics of the 12 ASL educators in our studies. Participants had a mean age of 46.8 years and an average of 14.3 years of teaching experience. The sample was predominantly women (75%), with 25% men. One-third of participants (33%) taught in public institutions, while 67% taught in private institutions. Regarding institutional classification, 42% were at R1 universities, 8% at R2 universities, 33% at Primarily Undergraduate Institutions (PUIs), and 8% at other institution types. Cells containing two IDs indicate educators who participated in both an interview and a focus group.

ID	Age	Gender	Years of Experience	Prior Familiarity with SL-AI	Type of Institution
I1, F1	56	Woman	34 years	Somewhat familiar	Private, R2
I2, F2	36	Woman	11 years	Moderately familiar	Private, PUI
I3, F3	67	Woman	25+ years	Not at all familiar	Private, PUI
I4, F4	38	Man	9 years	Not at all familiar	Public, R1
I5, F5	37	Woman	5 years	Not at all familiar	Private, PUI
I6, F6	44	Woman	9 years	Slightly familiar	Public, Other
I7	54	Man	20 years	Somewhat familiar	Private, R1
I8	61	Woman	10+ years	–	Private, R1
I9	40	Woman	17 years	–	Private, PUI
I10	61	Woman	12 years	–	Private, R1
I11	37	Woman	12 years	Not at all familiar	Public, R1
I12	31	Man	7 years	Somewhat familiar	Public, R1

During our focus group sessions, we asked participants about how AI could create more expressive and receptive learning applications and discussed AI as a conversational partner for practicing ASL. Finally, we invited participants to share additional thoughts.

3.4 Analysis

A senior ASL interpreting student on the team translated the interviews from ASL to English. Another team member, a native Deaf signer, reviewed the transcripts for accuracy. Initially, two HCI researchers assigned codes to the transcripts using Google Docs. The interpreting student who conducted the interviews subsequently reviewed these codes.

To facilitate remote collaborative data analysis, one of the HCI researchers organized the codes assigned to each participant's transcript in Miro.[4] Through multiple iterative discussions, we further analyzed the interview data and collated the themes in a spreadsheet. The team conducted three one-hour meetings to discuss the codes assigned to each participant's transcript, during which notes and memos were taken. Following these discussions, one of the team members led further data analysis using Braun and Clarke's reflexive thematic analysis approach [26, 27], resulting in the creation of themes and sub-themes.

An interpreter assisted with the transcription of the focus group sessions. After the sessions, a graduate student researcher, who was a native Deaf signer, reviewed the transcripts, making necessary edits. Three HCI researchers coded the transcripts, which were reviewed by the Deaf graduate student. The analysis involved a reflexive thematic analysis approach, similar to the steps outlined above for the interview analysis.

3.5 Positionality Statement

Our research team includes both hearing and DHH members. The team includes both men and women. Among the hearing members, two have taken eight or more advanced ASL and ASL/English interpreting courses, while two have taken introductory ASL courses. Most team members learned sign language in the northeastern United States. All members of the team are accessibility and HCI researchers with advanced degrees or are currently pursuing graduate degrees in computing, except for two who hold advanced degrees in ASL interpreting and linguistics, respectively.

4 Findings

During the formative interviews and follow-up focus groups, participants drew upon their extensive experience teaching ASL to share where they felt AI could meaningfully support ASL learning, while also cautioning against its uncritical integration into existing pedagogical practices. Their familiarity with AI, however, varied—some were well-versed in its emerging applications, including in ASL education (I10), while others were just beginning to encounter it: "*I never really thought to look for AI for ASL. Any AI to come out has been pretty new so far, I'm only noticing it now.*" (I6). As a result, our studies surfaced essential fundamental, ethical, and linguistic considerations for AI technologies in ASL education, presented in subsections 4.1, 4.2, and 4.3.

We also discuss categories of potentially useful AI-based tools—some creative and speculative, others more immediately feasible. We present more concrete use cases in our findings in subsections 4.4 and 4.5 that could inform specific design and research efforts. The two most prominent such use cases ideated were tools for supporting independent learning by providing automatic feedback on signing and tools for enabling conversational practice, which we explored in greater depth during focus groups. Figure 1 illustrates our findings through a thematic map.

Findings from the focus groups informed the design implications in Section 6, and at key points in the following subsection we link to the corresponding design insights developed through our reflection on these findings.

[4] Miro: https://miro.com

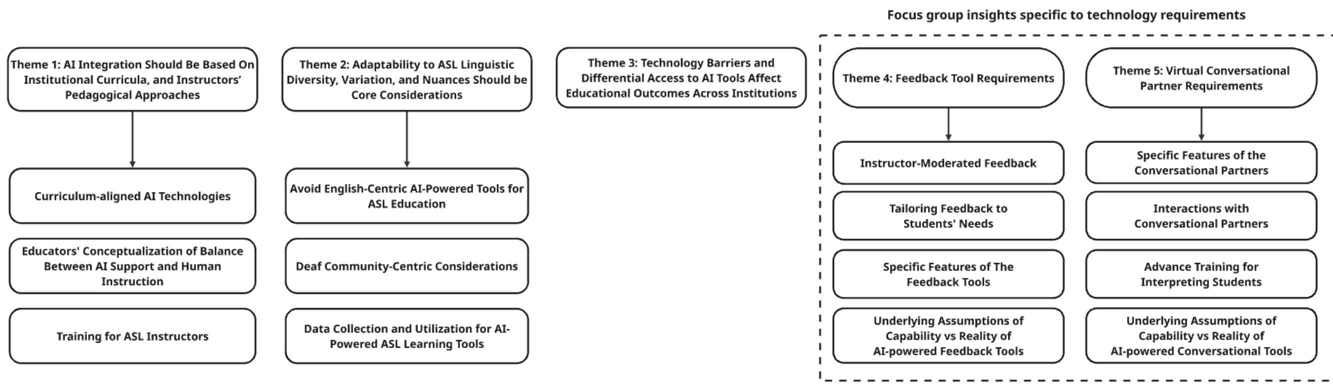

Figure 1: A thematic map of our findings illustrating themes and sub-themes. Themes 1–3 are not tied to specific ASL learning technologies. Themes 4 and 5 focus on specific tools and present insights that follow the preamble, drawing primarily from focus group findings where participants were briefed on AI-based ASL tools to ensure they understood their capabilities and limitations.

4.1 AI Integration Should Be Based on Institutional Curricula, and Instructors' Pedagogical Approaches

ASL instructors mentioned that for AI to be successfully integrated into ASL education, it must align with existing pedagogical practices and tools familiar to educators and students.

4.1.1 Curriculum-aligned AI Technologies. Participants stressed that AI-powered tools for ASL education must align with institutional curricula. They believed collaboration between AI and teachers is essential, with educators overseeing the process. For example, I6 stressed that AI should not automatically create grading rubrics for assignments; this should come from educators.

Instructors also saw value in incorporating AI into existing widely used platforms like "*Kahoot, GoReact,*[5] *and Quizlet*." (I6). To do so, participants emphasized that the AI-powered technologies require understanding and aligning with the curriculum used: "*We want to make sure it can understand the curriculum we're using. Are we using TWA (TRUE+WAY ASL*[6]*)? Are we using Signing Naturally?*[7] *Are we using Deafined?*"[8] (F5).

4.1.2 Educators' Conceptualization of Balance Between AI Support and Human Instruction. Participants often described AI as a textbook tool, where it is envisioned to be like an answer key. In this vision, students can use AI for self-checking, rather than replacing their instructor. In more detail, moderation does not mean that educators must verify every AI-generated response, but instead, it involves trusting the "answer key" to be reliable, thereby truly reducing some of the instructor's burden. F4 highlighted this vision and elaborated:

> "*It's going to add in an additional amount of time at the beginning, you know, to kind of get used to it, and then over time that workload will balance out, and our workflows will get more efficient.*" (F4)

Similarly, instructors expect AI to help with balancing their workload, especially when teaching large-scale classes:

> *I do think it would help to lessen the burden, especially with a large class of students, making sure that we are helping them to be successful, which is our main goal in the end; giving individual feedback is a lot. But we want to be able to use it (AI) as a tool.*" (F6)

In this sense, AI was framed as "*a teacher's assistant*" by F4. Therefore, instructors' views suggest that moderation means: (1) setting the initial parameters for AI use (e.g., what to grade based on the curriculum, grading rubric, what to highlight in feedback, etc.), and (2) shifting the instructor's role from generating all feedback from scratch to "*tweaking*" and refining AI-generated suggestions. This conceptualization of balance maintains instructor authority and pedagogical approaches, while benefiting from AI to reduce workload.

4.1.3 Training for ASL Instructors. An essential factor for instructors to use and moderate AI tools effectively is a clear understanding of how the AI technology operates. Multiple participants from both studies emphasized the need for proper training, research, and resources on AI usage for ASL education, highlighting the role that academic institutions should play in providing these in the future. Such training was discussed for everyone who uses the AI technology, whether the leaders or the educators:

> "*We'd have to develop a course for the students to teach themselves ASL, or just how to use the AI. Or if there was a career called 'AI for ASL', if there's a job for that, that means that whoever researched it needs to prepare me on how to teach my students about it.*" (I5)

For instance, I8 discussed "*workshops that will show me how to properly use it (AI)*" highlighting the importance of educating instructors on AI and its applications.

[5] GoReact: https://get.goreact.com/sign-world-languages/
[6] TRUE+WAY ASL: https://truewayasl.com/
[7] DawnSignPress Signing Naturally: https://www.dawnsign.com/series/details/signing-naturally
[8] ASLdeafined: https://www.asldeafined.com/

4.2 Adaptability to ASL Linguistic Diversity, Variation, and Nuances Should Be Core Considerations

The majority of our participants emphasized that ASL is not static; instead, it varies regionally and evolves over time. Instructors emphasized the need for AI systems to keep pace with these differences and changes, enabling the technology to be aligned with the Deaf community and appropriate for ASL education. One example of ASL's non-static nature was brought up by I11, highlighting the importance of representing regional variation: "*If a student self-taught from YouTube, you'd notice how their signs would be differing in regionality; you could learn all the variations and become more well-rounded. Can AI [characters] offer that?*" This underscores a critical challenge for AI in ASL education: supporting linguistic richness and diversity.

4.2.1 Avoid English-Centric AI-Powered Tools for ASL Education. Instructors also pointed out that AI might continue to impose English linguistic constraints on ASL, similar to some of the current ASL learning resources, e.g., sign language dictionaries. Instructors worry that AI would repeat those issues, particularly regarding the dominance of English-centric ASL resources:

> "*They need to develop a dictionary that doesn't focus on only English words, rather it puts and explains signs, describes the context of that sign [...] For example, the word* RUN*, many people assume* RUN *means a person running with their legs. But what about a car running? Or a nose running?*" (I12)

These insights show that the concern is that AI technologies might inherit the limitations of English-based resources and scale those limitations across new ASL learning tools, reinforcing English-dominant contexts rather than ASL-specific nuances or semantic richness.

4.2.2 Deaf Community-Centric Considerations. Following up on the concerns regarding English-centric ASL resources, instructors noted that the Deaf community is very diverse and future AI tools must reflect that diversity to remain relevant and useful. They emphasized the need for Deaf ASL experts to be centrally involved in the design, development, and deployment of AI for ASL learning. In addition, instructors advocated for including "*linguistics stakeholders..., and that means Deaf individuals who have strong understandings of ASL*" (I10). This insight was echoed by multiple participants, where efforts to design learning tools should be led and supervised by Deaf experts. Importantly, participants raised concerns about lacking input from those with ASL pedagogy expertise, asking, "*Are they [creators of AI] already expert curriculum developers? Or... only computer science majors?*" (I1). For example, I3 pointed to the role of expert communities or associations like ASLTA in guiding AI development through shared regional insights.

4.2.3 Data Collection and Utilization for AI-Powered ASL Learning Tools. Our participants from the interviews highlighted additional important considerations for AI-powered ASL technologies and shared their views on the types of data suitable for training the machine learning models underlying the system for sign language education. Instructors underscored the challenge posed by the limited data sample available for learning sign language compared to spoken languages, emphasizing the need for careful data consideration since "*a very small percent of the entire world uses sign language.*" (I2). In addition to the sparsity of data on sign language for model training, instructors highlighted that *whoever* contributes to the data used for training matters significantly; instructors emphasized that the underlying models for ASL technologies should be trained on quality data sourced from the Deaf community and expert ASL educators. In their view, centering Deaf signers and ASL educators in the training corpus is essential not only for improving the viability and pedagogical usefulness of AI tools but also for ensuring that these systems reflect community norms, linguistic nuances, and are culturally grounded.

4.3 Technology Barriers and Differential Access to AI Tools Affect Educational Outcomes Across Institutions

Participants from both interviews and focus groups raised concerns about technological challenges and equity issues with AI-powered ASL tools.

Instructors shared their views on technological barriers, equity issues, and power structures behind AI deployment, highlighting that such educational AI-powered ASL tools may create a divide. I3 noted, "*Here where I work, we don't have the best technology. If the AI breaks down, what do we do?*" pointing to infrastructure limitations that could disrupt education opportunities. Participants further highlighted the divide in socioeconomic status and presented a concern about fair access across educational settings. Such a divide was discussed to disrupt the feasibility of implementing such tools in high schools compared to colleges, emphasizing the need to protect fair access. In addition, our participants noted that discussions about AI use are not prevalent among ASL teachers, and decisions about employing AI technology often require consensus, even within smaller groups such as departmental educators.

Building on these concerns, focus group participants broadened the view, pointing to the infrastructural concerns and power imbalances. There were questions raised about who controls and funds AI systems in educational contexts: "*Where is this technology coming from? Who's providing the equipment? How would that work, exactly?*" (F6). This concern was similarly pointed out by F1, anticipating substantial institutional costs for obtaining the new technology and training on how to use it. Participants frame AI not only as a technical innovation in ASL education but also as a resource-intensive infrastructure that could repeat existing power imbalances in higher education.

Following up on this line of discussion, F2 expressed their concern about the lack of equity in long-term access and social stratification:

> "*It could get a paywall after a while [...], and anyone who's going to be able to use that needs money and education. So, someday in the future, is it still going to be accessible? [...] you see the same kind of access to colleges, a privileged situation. So that divide... I could envision in this context becoming even worse.*" (F2)

These accounts show that AI is not considered only as a pedagogical tool but as a technology that may deepen existing inequities in access to education if questions of funding, infrastructure, and long-term affordability are not addressed.

4.4 Feedback Tool Requirements

Following up on the discussions about concerns and opportunities of using AI for ASL education, interview participants frequently mentioned opportunities for using AI to provide feedback on signing.

In this subsection, we highlight key design insights primarily derived from focus groups. Instructors were not anti-AI, but they were conditionally enthusiastic, only if AI could reliably handle the job.

Participants emphasized the importance of feedback: "*If I don't provide feedback, the student will forget!*" (I3). Participants also appreciated the flexibility AI could offer by providing timely, initial feedback outside of scheduled class hours. As I9 noted, "*...the start and stop time of your lesson would be up to you.*" Instructors described how AI could support self-assessment by allowing students to record, review, and compare their signing for structured reflection. This enables students to develop self-awareness and refine skills, where AI could assess homework

Others highlighted the value of AI as a classroom assistant, especially in larger classes where giving individual feedback is challenging. AI was also envisioned to be used as a teaching assistant, offering support on preliminary drafts. As I12 explained, "*some colleges have 30, 40, 50 students [in class]! It'd be useful if AI could give feedback to students, only for rough drafts though… For final draft videos, I'd go through it and give feedback*".

When it came to feedback content and signing aspects, some instructors saw promise in AI providing support for beginner-level skills such as fingerspelling and basic sign structure. Others expressed skepticism about AI's ability to evaluate more complex aspects of ASL, such as full sentences, non-manual markers, and mouth morphemes. Instructors' expectation of a reliable AI feedback tool is one that can capture and reflect on expressive nuances, non-manual markers, etc., beyond mere feedback on signs: "*If AI can only give feedback on signs, it's not that helpful. AI would need to help them learn grammar, NMM, body shifting, use of space, and all the other aspects of ASL. If it could help them with that, it would definitely help!*" (I7). In general, instructors stressed the importance of addressing these elements for AI tools to be truly effective:

4.4.1 *Instructor-Moderated Feedback.* DESIGN INSIGHT #1

In light of AI-powered feedback tools, instructors acknowledged it would be hard to fully rely on AI, and emphasized their own role in maintaining moderation over AI feedback. The primary concern highlighted was the AI feedback's accuracy, especially in automatic grading, and its alignment with instructor expectations: "*we would always have to go back and double-check*" (F6), as there is uncertainty about AI being a perfect tool. Notably, instructors believed that their oversight of AI feedback could allow for better utilization of what the tool will offer:

> "*We are still the ones that are in charge [...] overseeing this entire process, and we can be more focused on the higher level, making sure that things are going smoothly, making sure that corrective feedback is happening, and utilizing what AI has given us in the end.*" (F4)

Participants also saw promise in using AI during students' practice sessions before teacher evaluations. AI was perceived as a tool that could share responsibility with instructors, and assess homework under instructor supervision: "*The [AI] model could help with receptive analysis homework and self-analysis, like a math textbook with an answer key*" (F1). F1 emphasized that this offers additional independent learning opportunities, as well as reducing the instructor's workload while maintaining oversight.

4.4.2 *Tailoring Feedback to Students' Needs* DESIGN INSIGHT #2.

Participants in the focus groups shared more in-depth views, noting that AI feedback should be tailored to students' contexts, including regional accents: "*Would the AI understand me the way I would sign here in [city name anonymized]? I feel like it would have to be more focused on my style and the way that we sign regionally.*" (F2).

Student proficiency level was also framed as an important factor in AI feedback tools; AI should recognize whether a student is an L1 (native signer) or L2 (a second-language learner) and provide feedback accordingly. Instructors argued that an AI that distinguishes regional variations could especially benefit L2 learners, where it does not simply correct errors, but supports comprehension across experience levels: "*who may find it harder to recognize subtle differences compared to native L1 users. By enhancing learners' receptive skills, AI can bridge gaps in understanding between individuals with different levels of language experience.*" (F1). Participants also emphasized that feedback should be aligned with the learners' stage in the curriculum. For example, F2 emphasized that feedback should match the student's level; for first-year students, focus on parameter errors such as handshape or palm orientation.

In this view, AI should also be able to differentiate between interpreting students and those in introductory courses. F4 highlighted feedback should account for students' "*vocabulary fluency,*" emphasizing different concepts for different words in ASL, and adapting to their focus area, whether general ASL or specialized fields like interpreting. F4 further suggested tailoring AI-supported learning to students' majors, as they do in their own practice:

> "*I try to teach signs that might be applicable to their majors. So is this an engineering student? Is this a nursing student? Is the student planning on going to the military? So I try to develop curriculum and vocabulary that goes along with their major, and then often they will have a more positive experience because it'll be more applicable to what they are learning, and then they are more likely to continue using that.*" (F4)

According to our participants, AI's feedback needs to be tailored to students' needs and levels for positive outcomes.

4.4.3 *Specific Features of The Feedback Tools.*

Textual and Visual Feedback DESIGN INSIGHT #3. The consensus in both focus groups was that the feedback should be both textual and visual. F5 argued that text is important, benefiting students with low vision. However, visuals are important, particularly for novice students relying on visual markers to understand key concepts. F3 added that without specifics on facial grammar, hearing students may struggle to grasp the feedback.

Feedback Language DESIGN INSIGHT #3. Participants highlighted that initial AI feedback for beginning ASL learners should be in the learners' first language, aligning with well-established scaffolding practices for second-language (L2) learning. Since ASL learners are typically L2 learners with English as their first language, instructors often referred to English as the language of initial AI feedback.

Instructors especially emphasized the importance of L1 use when students are still building foundational skills, and as students' receptive skills improve, feedback can transition into ASL, tailored to their proficiency: "*I believe it (feedback) should be in their 1st language, especially in the early stages*" (F2). This approach follows the pedagogical scaffolding for L2 learners for any language as emphasized by F4: "*We want to think about things with a linguistic perspective.*"

Instructors also highlighted feedback language for interpreting students specifically: "*I do work with interpreting students, and therefore they are bilingual students [...] we can give that (AI tool) to those students, and they are able to listen to the English version first*" (F1). F1 underscored the importance of bilingual feedback, envisioning it to support bilingual workflows where students can access feedback in English while engaging with ASL content.

Time-stamped Feedback DESIGN INSIGHT #3. Participants also emphasized the importance of assigning feedback to specific moments in students' signed production. They suggested that video feedback should be timestamped, as in existing software: "*Imagine you have captured a video, and you're looking at the time of the message. It would maybe have a timestamp and written feedback that the student could look back at to see the feedback*" (F2). This would help students to better understand and apply the feedback provided.

Correct Performance DESIGN INSIGHT #4. Participants also highlighted that AI feedback should not only flag errors, but it should include correct performance examples as well. F5 argued that: "*If the AI catches a signer making an error, it should model the correction, like an interactive video.*", believing that this approach is important to give students a better understanding of signs and to reflect on their own performance. F4 similarly framed AI-generated corrections as part of an ongoing instructional process: "*I will work with them to make sure they are producing these signs correctly, and this AI feedback will be a part of that post feedback.*" These perspectives show that AI is not merely expected to be used as an evaluator, but as a tool that can provide correct guidance to support students' revision and skill development.

4.4.4 Underlying Assumptions of Capability vs Reality of AI-powered Feedback Tools. Instructors believed that AI-based feedback would be considered viable in ASL education if it approached perfection, particularly in its ability to detect and evaluate signing errors. As F1 stated, "*Can AI be 100% perfect? Can it detect every error? I'm not sure if AI would be ready for the level that we could use in the classroom.*"

Here, AI is imagined as a comprehensive evaluator of student signing, and anything less than full accuracy raises doubts about its suitability for educational use in ASL. In addition, instructors expressed curiosity about whether AI will be able to detect regional variations in ASL linguistics, highlighting it as a demanding threshold beyond catching errors in signing. ASL feedback evaluation was envisioned to include interpreting structural and regional variation within the Deaf community as well:

> "*So in the community, we see many different structures. So it's difficult for me to imagine how AI would be able to catch these differences from the community. A Deaf person can see it and understand those differences in structure. So I'm not sure if AI would be able to learn how to evaluate that.*" (F2)

In other words, a "perfect" AI would not only need to recognize incorrect signing but also understand correct and legitimate linguistic structure variations. According to F5, accuracy remains a critical condition (*"If the AI could do that accurately"*).

In general, these accounts show a tension between instructors' enthusiasm for AI's potential to reduce barriers and their skepticism about its current ability to meet the high standards in ASL education. AI is seen as promising, but its adoption remains dependent on thresholds of accuracy and judgment aligned with various ASL structures.

4.5 Virtual Conversational Partner Requirements

The second prominent use case for AI-powered ASL technologies was conversational tools to support signing practice. ASL is a rich and complex language, and participants emphasized that effective learning requires more than vocabulary memorization—it involves full linguistic and communicative development. I10 highlighted the need for an interactive AI toolbox that enables learners to engage in comprehensive language practice, not just isolated assessment drills. AI-powered tools that facilitate conversation practice could help foster independent learning and skill refinement. As I12 noted, interacting with an AI conversational partner would offer more effective practice than simply watching videos, helping students "*improve their signing skills and gain more confidence.*"

While educators underscored the importance of in-person classes and social interactions with the Deaf community, they also saw AI-powered conversational tools as valuable complements for out-of-class practice, reducing barriers to practice. Such assumptions were grounded in the widely shared challenges in ASL education, specifically, students' difficulty finding practice partners outside of class time. As a result, instructors were generally aware that an AI conversational partner is not equivalent to a human, but they framed such a tool as preferable to having no practice partner at all. F6 described conversational AI partners as "*a chance to practice in the interim*," showing how instructors imagined AI filling gaps, even as they acknowledged the technology's current limitations.

Participants were excited about using virtual conversational partners to aid ASL learners. In our introductory presentation, participants were introduced to avatar and video-based conversational partners powered by sign LLMs [54], and their feedback addressed both approaches. F6 highlighted avatars' potential to expose students to diverse ASL accents and styles: "*Many students only encounter one Deaf person, often their professor... Using avatars could incorporate this diversity.*" Others agreed, noting avatars could showcase different regional accents. However, some cautioned that over-reliance on avatars or generative agents might reduce interactions with the Deaf community.

4.5.1 Specific Features of the Conversational Partners.

Warm and Culturally Adept DESIGN INSIGHT #5 & DESIGN INSIGHT #6. Participants noted concerns about the naturalness of AI-generated signing, referred to as 'robotic.' Thus, virtual characters should be warm, welcoming, and professional: "*...instead of just monotone or not smiling at all. Wanna make sure the personality is welcoming and warm and friendly*" (F2). F3 added that the virtual characters should react constructively to students: "*If the student asks a question, you want it to respond [...] 'Oh, that's a good question,' and then go on.*" Participants also advocated for culturally adaptive virtual characters that understand and reflect appropriate signals. For example, F3 noted that virtual characters "*definitely have to add the facial expressions and facial grammar, for sure.*" F1 further highlighted: "*Make sure that they're familiar with the social cues and the cultural contexts of the deaf community.*" F1 suggested that if these virtual characters are unable to grasp cultural context independently, they should be paired with an instructor who can provide the necessary context.

Avatar Customizations DESIGN INSIGHT #7. Participants emphasized that avatars should be customizable based on student preferences. F5 linked this view to how users can set voice preferences in speech systems. Such customization can include visual parameters like look, dress, signing style, and speed: "*Options of avatar or appearances that people could choose and customize*" (F3). In addition, F1 highlighted students' learning style, as "*Everyone has different learning styles and different personalities*". These accounts frame avatar customization as a way to align AI tools with diverse learning styles and comfort levels.

Diverse Characters DESIGN INSIGHT #7. Participants noted avatars could resemble "*a new student in the room*" (F4), and emphasizing having multiple signing avatars to reflect diversity. F2 suggested showing different signing styles side by side: "*So if we're thinking about Black ASL... You could see these differences shown next to each other.*" They highlighted expressiveness, cultural adeptness, and customizability as key, suggesting virtual environments with multiple characters to reflect diverse signing styles and cultural backgrounds.

4.5.2 Interactions with Conversational Partners.

Duration DESIGN INSIGHT #8. Instructors discussed how conversations with virtual ASL partners should be structured to align with students' attention spans:

> "*[College] students' attention span... they might go for 20 or 30 minutes. They're not able to do an hour, and an hour's not very effective. I used to work at ASL Connect[9]—20 to 30 minutes was basically all they could do. So if you want more, you can, but most attention spans are maybe max 30 minutes for an interactive situation.*" (F5)

In this view, virtual ASL practice should be designed around focused interactions rather than long, continuous sessions, to keep students engaged in the process of interaction.

Turn-taking DESIGN INSIGHT #9. Participants discussed incorporating effective active listening habits in conversational AI. As one participant noted, "*Some people don't mind just attending to a conversation, just listening and watching, other people want to be signing themselves the whole time... [the AI] could adjust itself to the student's preference*" (F3). They suggested that interruption frequency and response structures should be customizable. F3 added that virtual partners' interaction should not be "*flat and neutral, with no personality.*"

Use of Stories DESIGN INSIGHT #10. Participants suggested that virtual characters could enhance learning by sharing different stories in sign language. F4 noted: "*I think this [sharing stories] goes along with both receptive and expressive skills.*" Having an avatar share a story allows students to test their understanding by "*asking the students what that [the story] was about.*", and the AI could be interactive, showing different facial expressions and providing clarifications, offering many opportunities for engagement.

Overall, participants emphasized the need for virtual ASL characters to offer personalized, adaptive learning experiences, focusing on aligning interaction duration and turn-taking to individual student needs. Interactive storytelling may help enhance engagement and learning.

4.5.3 Advance Training for Interpreting Students.

Participants highlighted that AI could be valuable for interpreting students, exposing them to a broader range of signers and offering mentorship, as interpreting students might struggle with some of the translations.

Simulating Real-world Scenarios DESIGN INSIGHT #11. Participants discussed AI characters simulating various interpreting scenarios, like medical or legal settings, allowing students to practice interpreting in different contexts. F4 emphasized the importance of interpreting multiple signers with different signing styles simultaneously: "*the interpreter would have to get used to interpreting different signing styles at the same time, because often in the middle of an assignment, you'll have two deaf people, and one of them is understanding or isn't understanding.*" Participants highlighted that AI could broaden interpreters' exposure to diverse signers and offer mentorship, helping their understanding of Deaf and hearing signing styles. They also emphasized AI's potential to simulate real-world contexts, like medical or legal settings, allowing students to practice with multiple signers and diverse signing styles.

4.5.4 Underlying Assumptions of Capability vs Reality of AI-powered Conversational Tools.

When discussing AI as a virtual conversational partner, instructors were well aware of the limitations of such technologies at the moment. Some participants, e.g., F2, consistently described an aspirational version of AI: "*50 years in the future. Maybe that could happen [...] would it look like an actual real person... a robot that could sign, that could use facial grammar? [If yes], sure. Why not?*" In other words, instructors' design ideas were grounded in a future-facing vision about what AI should be able to do, rather than a belief that existing systems already meet those expectations.

Participants framed viability in using AI as conversational partners in terms of socio-cultural and personal appropriateness. F1 emphasized that any AI conversational partner used in ASL education would need to be deeply attuned to Deaf norms: "*You would want to make sure that they're (AI) familiar with the social cues and the cultural parts of the deaf community*" (F1). In addition to socio-cultural norms, F1 also expected the system to adapt to learners' different styles and personalities: "*Everyone has different learning*

[9] ASL Connect: https://gallaudet.edu/asl-connect/

styles and different personalities. So, [it's important to] have that avatar or robot be able to recognize those differences" (F1).

For interpreting practice in particular, bilingual features were emphasized as another important requirement for a useful conversational AI partner: "*[The] use of different bilingual modes too. So if you are more exposed to hearing things like Spanish and German, that sort of thing. That can be very helpful*" (F4).

Findings show that "good enough" AI is capable of navigating social, cultural, and interpersonal human nuances, and bilingualism in interaction. These accounts demonstrate a tension between educators' enthusiasm for using AI and current technological realities. Participants outlined ideal design requirements while intentionally staying skeptical about the current capabilities of AI technologies.

5 Discussion

Before presenting our design implications, this section situates our findings within broader HCI literature, ASL pedagogy research, and theoretical prior work on ASL technologies; a discussion of specific use cases and educator-ideated features appears in the standalone design implication sections 6.

Prior research has gathered requirements for ASL learning tools from ASL students [22, 66, 69, 167] and designed technologies to support their needs [14, 20, 65] (described in Section 2.2). ASL educators, especially Deaf educators, have rarely been meaningfully involved in research on AI-based ASL learning technologies. When they do participate, their contributions are often limited to tasks such as monitoring field studies [77] or creating and grading comprehension assessments [78]. Prior work (e.g., [45]) shows that sign language AI research at large frequently lacks intentionality, with problem framing and model design overlooking Deaf interests and relying heavily on interpreter-only datasets. Our findings underscore the need for early engagement to ensure linguistic, curricular, and cultural alignment. Our studies are among the first to engage ASL educators from higher educational institutions across the U.S. to understand their perceptions of AI-based ASL learning technologies. In doing so, we contribute to the rich literature on *educator-centered design* for language learning [31, 49, 63, 115, 125, 127, 130] technologies by broadening it to a sign language.

5.1 Cautious Optimism Towards AI

Educators across higher education hold varied views of AI, expressing both optimism and concern about its pedagogical impact and effects on student learning [8, 41, 87, 169]. Prior studies characterize their perception as "moderate acceptance" of AI—neither fully embracing nor rejecting it—while pragmatically adapting their pedagogical practices and remaining cautious about dependency and academic integrity [157]. Our participants shared this.

Our participants similarly had uneven knowledge of AI, requiring us to explain the capabilities and limitations of current AI-based sign language learning tools during interviews. Like other language educators [85], ASL educators sometimes described AI in human-like terms, yet they were quick to emphasize its potential for errors and the difficulty of achieving reliable ASL recognition or generation. This cautiousness may stem from previous negative experiences with underdeveloped ASL technologies.

5.2 AI's Potential to Reduce Workload

Optimism centered on AI's potential to reduce workload by offering automated feedback on video-based assignments—a major need given the heavy labor demands associated with grading video-based assignments and "cultural taxation" experienced by ASL educators, especially Deaf educators [126]. Pessimism focused on two areas: concerns that AI might diminish linguistic variation and cultural nuance, and worries about equity, institutional support, and adequate training. Echoing findings from other language-education contexts, our results suggest that responsible design alone is insufficient [63]; educators' concerns must be addressed through ongoing dialogue. Even so, participants offered actionable suggestions, including aligning tools with curriculum goals and ensuring appropriate training data, alongside design considerations discussed in the next section.

All participants were open to using AI tools to complement traditional learning methods—citing benefits such as time-flexible feedback, self-assessment, stronger information retention, and increased learner confidence. They were also optimistic about integrating AI-based supplementary resources as modules in their courses and existing ASL education systems, e.g., GoReact.[10] This optimism aligns with findings from other fields, where educators accept tools that help track learners' proficiency outside tutoring sessions [12]. Therefore, AI could also address another challenge beyond grading video-based work: ASL courses tend to rely heavily on summative assessments and offer fewer formative opportunities due to grading load [150]. AI could help shift this balance by enabling more timely formative feedback.

5.3 Customization and Adaptability

A major challenge highlighted by participants—and echoed in prior work—is that, unlike English or other spoken-language learning contexts with extensive theoretical and pedagogical research, ASL pedagogy remains fragmented and comparatively nascent. Teaching associations provide guidance, but they are not as large or comprehensive as those for spoken languages. As a result, many ASL educators rely on "trial-and-error" strategies [106, 126, 132, 141]. As outlined in Section 2.3, ASL teaching practices are more diverse and less standardized than those of spoken languages, making adaptability and customization even more crucial for classroom- or course-based AI tools.

Participants emphasized that educators should be able to customize these tools to fit their teaching styles and best practices in ASL pedagogy. They expressed concerns that 'black-box' systems may remove educator agency. Prior research also highlights the importance of designing AI systems that adapt to varied pedagogical practices [90, 124].

Our findings also align with theories of AI sensemaking that examine how AI reshapes the sociomaterial assemblage of learning—where tools, relationships, and pedagogical practices are intertwined [82]. As noted by Celik et al. [31], AI systems such as autonomous tutors can undermine learner autonomy and shift teacher–student dynamics. Deaf educators in our studies were particularly aware of these risks and stressed the need for educator moderation, student-level customizability, and curricular alignment. They viewed AI tools not as neutral artifacts, but as actors that

[10] GoReact: https://get.goreact.com/sign-world-languages/

must remain accountable to community norms, Deaf-led teaching practices, and equity considerations.

5.4 Challenges to Language Diversity

A key concern was that AI might fail to accurately capture regional sign variations, a challenge previously raised by ASL learners as well [65]. Participants also noted that AI-generated signing often appears robotic or unnatural, reflecting persistent issues in avatar-based systems [4–6], including inaccurate or missing facial expressions such as eyebrow and mouth movements [108]. When considering integration into formal learning environments, educators warned that relying heavily on such platforms may reduce a three-dimensional, spatial language to a two-dimensional medium, limiting learners' understanding of ASL's spatial complexity [117].

These concerns align with critiques that AI risks homogenizing linguistic diversity, but this issue is of a lot importance in the context of ASL, given the regional diversity and dialects. Dialects overrepresented in training data may become defaults, erasing variation and diminishing cultural, rhetorical, and epistemological richness. Educators in our study raised specific concerns that feedback tools may fail to recognize legitimate signing variations, while conversational tools might default to dominant dialects, posing challenges for learners when engaging with diverse Deaf communities [19]. To mitigate these issues, participants recommended involving ASL educators, Deaf individuals from varied regional backgrounds, and teaching associations such as ASLTA [13] throughout the development of AI-based tools.

5.5 Reflecting on the Role of ASL Educators in the Design of AI-based Learning Tools

Work on the design of AI-based learning tools for sign languages is still nascent. Computing research on ASL learning tools has mainly emphasized beginner vocabulary work [66] and feedback on isolated grammatical features such as non-manual markers [161]. Our findings highlight several needs that matter for classroom practice. Educators described how students struggle to move "beyond vocabulary" (i.e., from isolated signs to full, coherent production) and how limited class time constrains the depth of feedback they can provide. They also noted that students often lack practice partners outside class, which slows expressive and conversational development. These two pain points shaped much of the discussion in our focus groups and motivate the tool types we examine next: feedback systems that not only correct errors but also scaffold students toward more complex signing through richer guidance, curated vocabulary progressions, and instructional hints, and virtual conversational partners that support sustained, natural dialogue practice and help students move from isolated signs toward fluent, contextually grounded communication.

6 Design Implications

Research on AI applications in sign language technologies, such as communication tools for DHH individuals [56] and sign-language-based education [53, 109], has established Deaf-led practices and highlighted the importance of involving d/Deaf experts in designing sign language technologies. Addressing our research questions on AI driven use cases or features (RQ1) and alignment with best pedagogical practices (RQ2), we outline use cases and design/deployment considerations. Notably, we share eleven Deaf-educator-informed insights for developing technologies to support ASL learning in higher education. Based on the two most promising use cases identified in interviews and further explored in focus groups, we present four design insights for *Feedback Tools* and seven for *Conversational Practice Tools.* We also assign near-term or aspirational tags to each design insight informed by our technical understanding, the literature [23, 24], and our findings. Near-term refers to implications that can happen in the short term, while aspirational insights need more time, resources, and technological readiness.

6.1 Feedback Tools

Our participants suggested AI tools should extend beyond vocabulary to offer comprehensive feedback on grammar, non-manual markers, body shifting, use of space, etc. While research prioritizes receptive skills technologies, e.g., dictionaries [25, 66, 92] and video understanding tools [65], our findings emphasize the need for feedback tools that enhance expressive skills—an area where we have seen very little HCI and design work [68]. Formative work on underlying technologies in feedback tools has mainly focused on grammar and facial expressions, developing software that provides feedback on ASL grammatical structures such as topicalization, facial expressions associated with topics, yes/no responses, WH-questions, contrastive role shifting, and signing fluidity [77, 79, 145].

Instructor-moderated automatic feedback. Our focus groups show that ASL educators prefer a moderated use of feedback tools, with an educator always involved. Further, they highlighted that any feedback tools deployed in courses should align with curriculum standards and feedback requirements set by the course instructor. Future research should explore how sign recognition technologies that detect errors from student video input [89, 161] can incorporate active input from ASL educators.

Learner-customized automatic feedback based on context. Beyond instructor moderation, systems should customize output to learner backgrounds. Participants highlighted several good pedagogical practices they use when providing feedback to students with different backgrounds and program levels, such as considering learners' prior skill levels and program context (e.g., ASL vs. ASL-Interpreting programs). Recent work on chatbot-style AI-tutors for sign language learning similarly shows that learners benefit from adaptive feedback, e.g., focusing on different sign components depending on the learner's stage, underscoring the need for sensitivity in feedback mechanisms [89, 122].

Scaffolded bilingual and multimodal feedback. Participants suggested two forms of textual and visual feedback, with a preference for initial feedback in English that transitions to ASL as students gain proficiency, reflecting long-standing views of L1 as a pedagogical scaffold in L2 learning [18, 52] and empirical findings that learners benefit from L1-glossed or L1-supported feedback in technology-mediated environments [97].

AI-generated corrections to improve signing performance. Another novel independent learning tool discussed was systems that allow students to compare their signing with AI-generated translations. Previous research explored tools that present side-by-side comparisons of student-recorded videos with expert signer samples,

DESIGN INSIGHT #1 NEAR-TERM	*Design automatic feedback tools that allow instructors to tailor and moderate the criteria of AI-generated feedback.*	Sec. 4.4.1
DESIGN INSIGHT #2 ASPIRATIONAL	*Provide automatic feedback customized to a learner's background, accounting for their proficiency level, educational context, and regional sign language variation.*	Sec. 4.4.2
DESIGN INSIGHT #3 NEAR-TERM	*Ensure feedback is time-stamped and presented in both textual and visual formats. For novice learners, begin with feedback in a written language, gradually incorporating feedback in sign language as their proficiency increases.*	Sec. 4.4.3
DESIGN INSIGHT #4 ASPIRATIONAL	*Create technology capable of generating accurate signing demonstrations in response to learner-uploaded videos containing signing errors to help students identify and correct performance issues.*	Sec. 4.4.3

including modified videos where experts' faces are swapped onto participants to help learners visualize their own signing [68]. Participants envisioned AI generating "expert" videos to display alongside learners' performances, but educators cautioned that, despite recent progress [54], generative technology remains too imperfect for this use.

6.2 Conversational Practice Tools

Our participants recommended AI-powered virtual conversational partners for signing practice. During our focus groups, we presented underlying technologies that can be used to create these partners, including sign translation systems [24, 171] or future sign generation systems [54, 147]. The virtual character could be presented as an avatar or as a character in a generated video [54][11].

A common concern raised by participants in interviews was the lack of a human partner for independent practice. A well-designed, accurate, and responsible AI could address this issue, as learners would not be constrained by the availability of conversational partners. Notably, ASL users tend to cluster in areas with large Deaf communities or significant educational resources for DHH individuals, such as Washington, D.C., Rochester, New York, and Fremont, California [110, 118]. AI-powered conversational partners could be particularly beneficial to learners in rural and urban settings across North America, where there is less concentration of learners and ASL users.

Novice ASL learners often feel self-conscious about their signing, so a virtual conversational partner could provide a comfortable way to practice conversations before interacting with other learners or members of the Deaf community [107]. ASL educators in our focus group were highly optimistic about the potential of conversational ASL characters to provide much-needed additional exposure for ASL interpreters. While the development of AI for ASL translation is still nascent, our ideated use case parallels advancements in spoken languages where AI-driven virtual agents facilitate language practice [46, 136]. Such applications could enhance receptive skills, such as understanding rapid fingerspelling, thereby boosting learners' confidence and encouraging them to sign back as well [16].

[11] SignLLM project: https://signllm.github.io/. The "Qualitative Presentation (Multilingual)" section shows sign language video generated through style transfer modeling under ideal future conditions.

Expressive virtual conversational characters. Our participants suggested that the virtual characters should be warm and friendly. In line with prior work on factors that motivate culturally deaf people to adopt assistive technologies [163], we found that linguistic and cultural alignment are important aspects for the adoption of AI-powered ASL conversational partners as educational tools.

Culturally diverse conversational characters. Like any cultural group, members of the Deaf community often share common values, behaviors, and traditions. However, no single Deaf person can fully represent the entirety of the community or its cultural nuances [23]. This diversity emphasizes the need for diverse representation and careful consideration of regionalism when designing technology for teaching sign language.

Customizable virtual characters. In addition to cultural alignment, the focus group discussions delved into the appearance of virtual ASL characters, the structure of interactions, and their role in advanced training for interpreting students. Participants suggested incorporating multiple virtual characters in the classroom to reflect the diversity of the signing community or the students themselves. They highlighted customizable features such as signing speed, style, and appearance. Prior work on making ASL translation systems more naturalistic uncovered some of these features, e.g., linguistic parameters such as pauses [6], speed and timing [5], as well as general appearance [159]. Our findings highlight the significance of previously identified factors in ASL translation research while also uncovering new factors relevant to the use of a virtual character for conversational practice.

Flexible conversation duration. A notable recommendation was that these characters should align their interaction duration with students' attention spans. Attention is an important factor in effective learning, and prospective AI applications to enhance and maintain attention among the learners [17].

Active engagement and personalized interruption frequency. Our participants also recommended that AI virtual characters provide learners with ample time to respond and offer constructive feedback, closely mirroring live instruction. Emphasizing the importance of turn-taking in ASL, participants in both studies highlighted its visual cues—eye contact and body movement—in contrast to the auditory cues of spoken language. Prior linguistic research using sequential and multimodal analyses has examined turn-taking [35]

DESIGN INSIGHT #5 NEAR-TERM	*Design AI-powered virtual conversational partners with warm and friendly personas to make out-of-class practice interactions more engaging, welcoming, and dynamic.*	Sec. 4.5.1
DESIGN INSIGHT #6 ASPIRATIONAL	*Virtual-generated characters should reflect the diversity of the Deaf community in terms of regional sign variations and cultural expressiveness, exposing learners to the rich diversity of signing and Deaf culture.*	Sec. 4.5.1
DESIGN INSIGHT #7 NEAR-TERM	*Allow students to customize the signing attributes, e.g., signing speed, and appearance of virtual characters based on their preferences.*	Sec. 4.5.1
DESIGN INSIGHT #8 NEAR-TERM	*Develop interactive conversational practice tools that allow users to modify conversational lengths to suit their availability and attention span.*	Sec. 4.5.2
DESIGN INSIGHT #9 NEAR-TERM	*Virtual characters on conversational practice platforms should support good practices of natural communication, such as active "listening", appropriate turn-taking, and interruption patterns.*	Sec. 4.5.2
DESIGN INSIGHT #10 ASPIRATIONAL	*Incorporate immersive storytelling elements in conversational practice platforms to improve receptive and expressive skills and assess them through references to story details during interactions.*	Sec. 4.5.2
DESIGN INSIGHT #11 ASPIRATIONAL	*Simulate diverse communication scenarios to help advanced students (e.g., ASL-English interpreting students) practice signing in specialized contexts, e.g., legal, medical.*	Sec. 4.5.3

and its acquisition [75]. For instance, studies show that turn-final holds frequently occur in turns strongly projecting a next action (e.g., questions), reflecting the speaker's expectations, with their release precisely timed to the discernible progress of that action [61]. These linguistic insights should guide the design of virtual conversational agents for practice.

Story-driven conversational practice. Participants also envisioned these characters engaging learners through immersive storytelling. Story designers and researchers are commonly using AI-powered stories for language immersion for other languages [120]. While gamification research in sign language acquisition [22, 94, 153, 167] has used characters and basic gamified elements like challenges, rewards, and levels, the potential for story-based scenarios, supported by AI model development [7], remains largely unexplored. Stories offer a valuable context for learners to expand vocabulary, practice advanced skills such as sign language spatial grammar [103] and classifiers [9], and assess comprehension in realistic situations [154], areas where sign language educators offer further insights into narrative-based pedagogy [37, 128, 155].

Simulating multi-signer contexts. There was also enthusiasm for the use of virtual characters in simulating complex interpreting scenarios, especially in medical and legal settings, where multiple interpreters with varying hearing abilities are present, and intricate turn-taking occurs. Some initial research has explored sign-language translation in healthcare settings [116, 139]. Similarly, ASL researchers have emphasized the importance of teaching signing in legal contexts [113, 137]; future research can further explore how best to design virtual characters to facilitate practice in these settings.

7 Limitations and Future Work

Our studies focused on understanding ASL instructors' perceptions of AI use in ASL education, including their views on what would constitute "ideal" or "perfected" AI in different contexts. Determining exact performance thresholds was beyond the scope of this formative qualitative work. Future research could examine performance expectations with ASL educators, as well as design challenges, features, interfaces, and interaction modalities.

Our focus groups were conducted online to support participation across the U.S. While we used visuals to illustrate how AI-based tools could support ASL pedagogy, participants did not directly interact with these tools, which may have limited understanding. Future work could use in-person workshops or provide educators with access to tools prior to getting their feedback.

We recruited participants through our academic networks and online platforms such as LinkedIn, which may have introduced self-selection bias, as educators with stronger interest in AI may have been more likely to participate. Although not addressed in this study, future work could explore recruitment strategies that reduce self-selection bias. Further, among participants who reported race, most identified as White. Because we did not ask for race in our interest form, we were unable to recruit more Deaf educators from other racial or linguistic backgrounds, such as BASL users [73] or those familiar with contact dialects like ASL–LSM [133]. Prior work likewise finds that ASL educators who participate in such studies are predominantly White/Caucasian [60, 112], underscoring the need for future research to recruit participants from these communities.

We interviewed only higher-education ASL educators to capture expert perspectives on AI in ASL classroom teaching. We did not include professional association experts (e.g., ASLTA), who could provide additional policy and broader, country-level insights into AI-based ASL education tools.

While ASL is taught across a range of institutions, this paper focuses on higher education due to the advanced and diverse content taught in these settings and prior work in higher education contexts [164]. As a result, our findings primarily reflect the perspectives of ASL educators teaching hearing students, though some participants reported teaching Deaf students and students with visible or invisible disabilities. Future research should examine ASL educators' perspectives in other educational contexts and explore how AI could support teaching sign language to d/Deaf students and children, as well as diverse-ability classrooms.

ASL is one of over 150 recognized sign languages and was the focus of this study due to its prevalence in the U.S., our familiarity with ASL and its educational context, and the availability of ASL-fluent researchers. Future work could examine educators' perspectives across other sign language communities.

8 Conclusion

While significant research has explored the use of AI in ASL education, most studies have primarily focused on insights from ASL learners. Our studies are the first to gather perspectives from expert ASL educators across the U.S. on the potential, risks, and future direction of AI in ASL education. Our work lays the foundation for an ASL educator-centered AI agenda and sets future directions for the design of AI-based tools to support ASL programs in higher education.

Our focus groups examined two key categories of AI use cases that are either currently feasible or will be soon: feedback tools and conversational practice partners. We provide eleven insights for the design of these technologies and considerations for their deployment. Future research should engage ASL educators, teaching associations, and the Deaf community through participatory and longitudinal approaches to design AI-based ASL learning technologies that are customizable, adaptable to diverse curricula, and responsive to linguistic variation across regions and communities. Such work should examine how these systems can be responsibly integrated into classroom practice while preserving educator agency, supporting pedagogical goals, and addressing equity, access, and real-world educational impact.

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A Description of Focus Group Slides

We designed a slide deck to present at the start of the focus group session. Our Deaf team member delivered the presentation. We summarize the slide descriptions below:

Slide 1: Title slide with the title "Introduction to Digital ASL Learning."

Slide 2: A bulleted agenda summarizing the structure of the presentation and focus group.

Slide 3: Text reading "What is AI?"

Slide 4: Defines AI as "A method where machines are taught to perceive their environment, learn from it, and choose actions most likely to help achieve a goal."

Slide 5: Slide explaining the first part of AI, titled "Perceive their environment," with detailed text stating "Capture and represent the world in a way that is useful for a computer." Decorative images emphasize AI's application in perceiving the environment, including a person speaking into a microphone, a thermometer, a surveillance camera, a GPS antenna, and text.

Slide 6: Slide covering the middle part of AI, titled "Learn from it," with detailed text stating "Analyze the collected data." Two decorative images of a connected mesh of links and numbers are included.

Slide 7: Slide describing the final part of AI, titled "Choose actions most likely to help it achieve a goal," with detailed text stating "Use the identified patterns to predict new outcomes as the environment changes." Decorative images include a robot, a cleaning machine, and a personal assistant device.

Slide 8: Slide titled "Immersive Reality" with the subtitle AI for Sign Language."

Slide 9: Slide titled "Immersive Reality (AR/VR/MR)," describing a 'Virtual Reality (VR) learning environment that enables immersive interaction with avatar signing characters and provides real-time feedback for ASL learners. The characters can sign basic words and point to objects. Figure 2 from [7] is shown, depicting a 3D coffee shop environment with a signing avatar indicating the sign referent before signing

COFFEE. Figure 2 from [131] is also presented, featuring a teacher avatar and the hands of a student avatar attempting to imitate the teacher's signs.

Slide 10: Slide titled "Receptive Feedback Tools," describing how video-based dictionaries allow learners to sign in front of a webcam, with the system providing the closest matching sign(s) and additional linguistic information. An annotated image of a video-based ASL dictionary, Figure 1 from [20], is presented.

Slide 11: Slide titled "Receptive Feedback Tools," presenting an annotated image of a video-based ASL comprehension tool, Figure 1 from [65].

Slide 12: Slide titled "Feedback Tools" with the subtitle "AI for Sign Language."

Slide 13: Slide titled "Expressive Feedback Tools," explaining that some preliminary tools can analyze learners' recorded signing videos or short narratives and provide feedback on specific aspects like head position or facial expression (e.g., eyebrow movements). Figure 2 from [68] shows screenshots of feedback videos with an expert signer on the left and the participant on the right. Feedback includes an arrow pointing to the learner's face, zooming in to highlight the moment an error in facial expression occurs.

Slide 14: Slide titled "Conversational Partner" with the subtitle AI for Sign Language."

Slide 15: Slide titled "Conversational Partner," describing future developments where ASL conversational partners could allow learners to practice short conversational sequences with an avatar. Research has highlighted the importance of optimizing the fluency, speed, and timing of signing avatars. Decorative image from [54] is also presented.

Slide 16: Slide titled "Conversational Partner," mentioning that researchers have recently proposed SignLLMs (Sign Language-Large Language Models), which could automatically produce sign language videos and engage in conversations with learners using sign language.

Slide 17: Slide with the subtitle "AI for Sign Language."

Slide 18: Content suggesting that in the future, with advancements in video-to-text machine learning models, it might be possible to create scene-based videos using AI. An example from the webpage for OpenAI's under development video-generation model, Sora, is provided.

Slide 19: Concluding slide with a recap of the agenda. Key points include "AI for Learning and Feedback" and "AI as a Conversational Partner," followed by a final item, Final Comments."