Signing for Care: A Demo and Initial Evaluation of an American Sign Language Learning Tool for Emergency Medical Service Providers

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Abstract

Deaf and Hard of Hearing (DHH) people often face significant barriers in medical settings, leading to miscommunication and reduced access to care. While American Sign Language (ASL) interpretation is essential for effective communication with DHH signers, it is frequently unavailable in emergency contexts. Emergency Medical Responders (EMRs)—frontline responders trained to deliver basic emergency care—often struggle to obtain accurate medical histories, particularly from DHH people with limited English literacy. To address this, we designed an AI-based ASL learning tool tailored for EMRs, featuring medical vocabulary modules and AI-powered vocabulary testing support. We present a preliminary evaluation of the tool with five EMRs and publicly release a working prototype with this paper. Insights from the study inform new features and vocabulary expansion.

CCS Concepts

• **Human-centered computing** → *Accessibility technologies*; **Empirical studies in accessibility**.

Keywords

American Sign Language, Sign Language, ASL, Sign Language Learning, Emergency Medical Services, Emergency Medical Responders, EMR, EMS, EMT, Vocabulary Learning, Dictionary, Communication in Emergency Settings, First Aid, Healthcare

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1 Introduction and Related Work

The various challenges faced by the DHH community in medical settings are well documented, ranging from procedures conducted without full consent to critical errors in medication schedules [2]. In a study, a DHH participant shared that medical professionals *seemed to be fine with just trying different medicines on me without first figuring out why I was going through this*; a fundamental breach of patient autonomy [17, 18]. As a result, DHH people face increased risk for a wide range of physical and mental health conditions [11]. The lack of trust and underutilization of medical services in these communities are closely tied to inadequate communication with healthcare providers.

Although ASL interpreters are preferred by DHH people who use ASL as their primary language, ensuring their availability—particularly in emergencies—is often challenging. Medical centers commonly rely instead on writing, rather than providing proper accommodations [16]. Higher emergency department utilization among DHH people compared to the general population further underscores the importance of accessibility in emergency medicine [17].

Emergency Medical Responders (EMRs) are often the first to interact with DHH people during emergencies [1, 10, 21]. In one study, 83% of EMRs reported losing critical information when communicating with Deaf patients [18], and paramedics frequently struggled to obtain complete medical histories [3]. EMRs show strong receptiveness to communication training and technology; for instance, all 148 participants in a communication training study found it helpful even after three months [25]. Limited prior work on this topic includes tools allowing EMRs to display emergency-related phrases as video translations in ASL [7, 8] and a tabletop interface to facilitate medical conversations between a DHH people and hearing physicians [23].

However, no targeted learning platforms currently exist to support EMRs during initial interactions before an interpreter is available.

AI-based tools for ASL learning have been developed for a variety of learner groups, including DHH children [4], interpreting students and ASL learners in colleges [14], and parents or caregivers of DHH children [26]. These tools often include video-based sign language dictionaries [5, 13, 14] or linguistic feature-based search interfaces [6, 19]. Others learning tools provide performance feedback on recorded signing, such as feedback on grammatical structures or non-manual markers [15]. Learners tend to prefer tools that support independent learning and offer real-time feedback as part of the learning experience. In this work, we:

- Design and release a working prototype of ASL vocabulary learning tool for EMRs. The prototype includes several modules featuring signs relevant to EMRs, along with an AI-based automatic testing feature based on isolated sign recognition. We release this working prototype, including the underlying model, with this publication (shared as supplementary material with this submission).
- Present findings from an initial user evaluation with 5 EMRs. Our findings echo known communication challenges, offer feedback on the tool, and highlight suggestions for new features and vocabulary expansion.

2 ASL Learning Tool for EMRs

2.1 Vocabulary Selection & ASL Recognition Model

We selected 79 emergency-related glosses in consultation with an EMR student on our team. Among them, 70 glosses are from the ASL Citizen dataset [9], which has high quality gloss-video pairs. We supplemented it with 9 glosses from ASLLVD [22] to expand our vocabulary. We manually grouped glosses into nine modules. The categories are: 'Body Parts 1 (A–F)', 'Body Parts 2 (F–Z)', 'Symptoms 1 (A-I)', 'Symptoms 2 (P-Z)', 'Substance Related', 'Medical Terms (A-P)', 'Medical Terms (S-W)', 'Injuries', and 'Emergencies and Others'. For example, the 'Symptoms 1 (A–I)' category includes signs like `BLEED`, `CHOKE`, `COUGH`, and `DIZZY`, while 'Emergencies and Others' includes `ALARM`, `ALERT`, and `EARTHQUAKE`. The entire set of categories and list of signs is presented in Appendix A.

For the testing module, we used the Spatial Temporal Graph Convolutional Networks (ST-GCN) model provided with the ASL Citizen dataset [9]. ST-GCN achieves high performance on ASL Citizen (88.1% top-10 accuracy) and offers faster inference than the alternative open-source I3D model, making it suitable our real-time prototype system. We retrained the model using our dataset of 79 emergency-related glosses over 200 epochs with an Adam optimizer [27] at a learning rate of 1×10^{-3}. To handle class imbalance (due to variability in examples of 9 new signs), we applied weighted random sampling, setting weights inversely proportional to gloss frequency. Rest of our model pipeline was similar to [9]. Specifically, we used cross-entropy loss and a cosine annealing learning rate scheduler [24] with T_{max} = 150. We extracted 27 keypoints from hands and face using MediaPipe Holistic [20], then center-scaled and normalized them. We applied data augmentations (random rotation, shearing) and down sampled ~~videos to 128~~ frames.[1]

[1]The validation score of our model converged to 0.84. Our top-10 accuracy was comparable to the original model (88.1% top-10 accuracy).

2.2 Interface Design

Our web-based prototype consists of three main pages: '`Home`', '`Resources`', and '`Test`'. As shown in Figure 1a, on the '`Home`' page, users can select a category of signs they wish to study. The 'Resources' page contains instructional content, including ASL fingerspelling. Sign videos were adapted from [22]. The '`Test`' page provides feedback on the signing performance of users based on the selected category. Once users hit the category button on the Home page, they can navigate to the signing video modules according to the category. Users can learn the signs by watching these videos. After reviewing the signs, users can click the 'Test Your Knowledge' button to proceed to the testing phase.

Some of the design choices on testing page were motivated by prior work with ASL learners [12, 14]. On the '`Test`' page, users can record a video for AI analysis, as shown in Figure 1b. A term selected from the chosen category at random appears, prompting users to perform the matching sign. Once submitted, our tool analyzes the correctness of signing and displays whether it is correct or incorrect (shown in Appendix B). If users' first attempt is incorrect, a 'Try Again' button appears. After a second incorrect attempt, the system displays 'We will get back to it soon,' deferring the term until all other terms are tested, and then automatically proceeds to the next term. If a user signs correctly, the tool shows the signing video, provides a confidence score, and offers a 'Next' button.

We release both the interface and underlying model as supplementary materials with this demonstration paper.

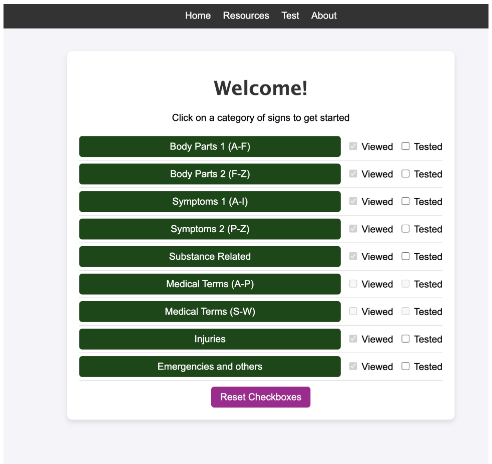
3 User Study Method

3.1 Study Protocol

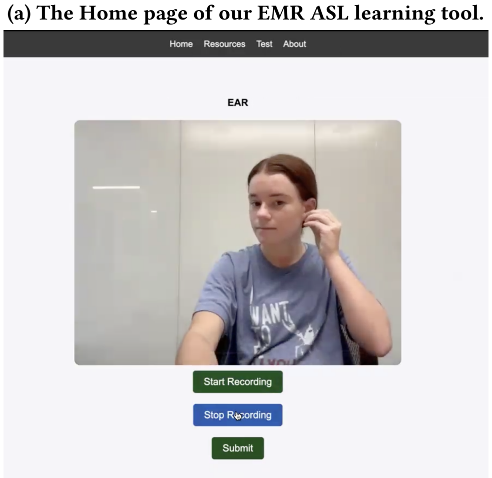
Participants signed an Institutional Review Board–approved consent form and completed a demographic and background information form before beginning the study. All sessions were conducted in person and comprised five parts. A researcher introduced themselves, explained the goals of the study, and requested permission to record the laptop screen (MacBook M3, 14-inch). Afterward, participants took part in an initial interview covering their current EMR role, experiences working with people with disabilities, and any prior experience or interest in learning ASL. Participants were then introduced to the ASL learning tool. The researcher demonstrated how to test one sign, after which participants were encouraged to explore the tool independently, test at least five signs, and think aloud while offering feedback. Participants were interviewed again, focusing on their experience with the tool—specifically viewing and testing signs, receiving feedback, and their overall impressions. They were also asked about desired vocabulary expansions, preferences for scenario-based or gamified learning, and thoughts on potential deployment platforms. Finally, participants were invited to share any additional comments. Although sessions were scheduled for 70 minutes, they typically ran slightly shorter. Participants received $40 for their participation. We recorded and transcribed all the interviews.

3.2 Participants

Participants were recruited through a university Emergency Medical Services organization. Five participants (2 male, 3 female) took part. Their average age was 21.2 years (σ = 0.45) and they had an average of 2.7 years (σ = 1.10) of experience as EMRs. All had



(a) The Home page of our EMR ASL learning tool.



(b) Participant signing "EAR" in the testing module.

Figure 1: Home page (a) is the landing page with vocabulary modules and test tracking. Testing page (b) includes a video recorder and provides users with feedback on sign accuracy. More images of feedback interface and UI elements are provided in appendix B.

elementary-level ASL experience, and two had completed some ASL coursework.

4 Findings & Key Takeaways

Due to space constraints, we present findings and takeaways to guide the next iteration of our tool rather than a full thematic analysis. These findings echo prior work on EMR communication challenges with DHH people [3, 18, 25] and issues with AI-based ASL learning tools [5], while also surfacing new suggestions for features and vocabulary.

4.1 Communication Challenges in an Emergency Medical Settings

Participants described communication challenges during emergency interactions and emphasized the urgency and rapid pace required. P1 highlighted the inherent stress, noting: "*it's more frustrating for [patients] because they're the one who needs help and you're not able to really provide the level of care that you normally would because you can't talk to them efficiently.*" P4 emphasized the difficulty of emergency interactions when patients cannot clearly express themselves, stating that *you have to use an intermediary.* Specific challenges were noted by two participants with DHH people, particularly elderly patients who are *either hard of hearing or legally deaf.* (P1). P5 mentioned that they need to ensure that *if they use hearing aids, and that they function.* A common strategy to address communication challenge was written communication, though P1 pointed out it *can be inefficient in urgent situations.* P5 suggested that ASL learning *should be incorporated into EMS training.*

> **Takeaway #1:** Participants mentioned that communication without an interpreter is challenging, and written communication can be inefficient in emergency settings, which highlights the need for basic ASL training for EMRs.

4.2 Feedback on the Tool

Participants feedback about the tool was overall positive. P1 appreciated the observational learning aspect, stating, "*I could watch someone do it repeatedly until I had it down… it was easy to memorize quickly.*" P4 particularly emphasized the ease of the use of the interface, and appreciated the video demonstrations, noting they were *really easy to learn.* P5 specifically praised the intuitive design and effectiveness of using video-based testing: "*the videos were a nice way to learn; I could do it a few times and I quiz myself up before moving on… it's intuitive way to learn.*"

As expected, given the imperfect nature of underlying sign recognition technology, participants encountered some challenges with sign recognition accuracy during testing[2]. P1 felt accuracy was generally good, remarking, "*it seems to be pretty accurate about if I did it correctly or not.*" However, three participants noted specific issues. P2 experienced frustration regarding signs involving their dominant left hand, commenting, "*I'm a lefty and a lot of the videos use their right hand… my gut instinct is to make the signs work with my left hand.*" Similarly, P5 expressed uncertainty, stating it was difficult to discern whether errors were due to incorrect signing or system recognition problems: "*it was hard to see if like I was doing something wrong or if it was just picking it up wrong.*" Despite these challenges, participants generally found minor adjustments sufficient to overcome inaccuracies, as P1 summarized, "*there were just a couple of times when it said it was incorrect, and so then I just kind of adjusted it a little bit… it was good after.*"

> **Takeaway #2:** Participants found the tool intuitive and effective, particularly the video-based learning, though they were sometimes uncertain if errors stemmed from their signing or system recognition issues.

[2] Median accuracy on five test signs (two tries) was 85.7% (σ = 16.85%), though participants weren't told to prioritize accuracy, given our focus on usability.

4.3 Suggestions for New Features

Participants provided several suggestions for enhancing the tool's usability and adding new features. P1 recommended adding adjustable playback speeds for videos, noting some videos moved "*a little fast.*"

Four participants requested **enhanced feedback** to better understand and correct their signing errors. P4 suggested that the system should offer corrective demonstrations when a sign is performed incorrectly, noting, "*maybe showing a video of how to do it correctly instead of just showing the video when you've done it correctly.*" P5 wanted more feedback to distinguish between user error *if the machine couldn't read it.* P2 expressed a desire for more personalized and instructive feedback, explaining, "*I almost wish I could talk to someone who knew ASL... it would be nice to know why it's incorrect so I can improve it.*" Similarly, P3 advocated for specific corrective cues to reinforce learning, such as *didn't touch all the way back.*

Regarding **scenario-based and gamified learning** approaches, participants provided nuanced perspectives. P1 was concerned that overly gamified experiences could detract from the learning process, citing popular language learning apps as potentially "*too much of like a game rather than actually actively learning something.*" P2 suggested realistic scenarios such as "*a 27-year-old man fell off a ladder*" or a scenario involving "*a college student outside of the [local bar] and he's really drunk,*" noting these scenarios could closely mirror real emergency calls. P4 suggested scenarios at the end of each learning module to test practical knowledge, mentioning, "*maybe it'll show you a patient with some affliction or injury... it'll test you on saying this patient has a broken left arm or something..., so you can apply what you've learned.*"

Participants also suggested incorporating **basic ASL grammar structures**. P2 recommended including essential conversational phrases, noting, "*I know ASL grammar differs a lot from English grammar... maybe how to construct phrases like, 'where is the pain?'*" P5 reinforced the value of incorporating conversational skills, recommending scenarios that involve basic interactions such as greetings, collecting patient identification, and symptom discussions.

Regarding **platform preferences**, participants preferred computer-based tools for better visibility and recording capabilities. P4 noted, "*I wouldn't want to have to do all that on my phone... more comfortable using the computer,*" while P5 added laptops are best *for learning... you can film yourself better, you can see it better*" and suggested "*an app to pull up on phone and look at when needed.*"

Takeaway #3: Some participants recommended adding (1) corrective feedback after each test sign and (2) real-world scenarios at the end of each module. Participants prefer large-screen platforms for better recording capabilities.

4.4 Suggestions for Vocabulary Expansion

Participants suggested several expansions to the tool's vocabulary. P1 recommended creating a dedicated category for medical terms and diseases to help obtain a comprehensive understanding of patients' medical history, stating, "*maybe a category for specific medical terms, like certain diseases, because we have to ask about medical history or medications, so we can get a bigger picture of the patient.*" P3 provided detailed suggestions, highlighting essential terms crucial for *emergency assessments, including allergies, medications, especially blood thinners, diabetes, seizures, heart attacks, strokes, high blood pressure, breathing problems, and asthma.* P4 emphasized the need for terms related to minor medical procedures, which frequently arise in EMS interactions. P5 suggested including practical conversational phrases and basic interactions such as greetings, patient calls, obtaining names, addresses, and time.

Takeaway #4: Participants recommended adding vocabulary covering medical history (e.g., conditions, medications), EMS procedures, and patient intake (e.g., name, address), along with conversational phrases for real-world interactions.

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A Vocabulary

(1) **Body Parts 1 (A–F)**: `ARM (Version 1)`, `ARM (Version 2)`, `ARM (Version 3)`, `BACK`, `BLOOD`, `CHEST`, `EAR`, `EYES`, `FACE`, `FINGER`, `FOOT`

(2) **Body Parts 2 (F–Z)**: `HANDS`, `HEAD`, `HEART`, `HEADACHE`, `JAW`, `LUNGS`, `MOUTH`, `NECK`, `NOSE`, `RIB`, `WRIST`

(3) **Symptoms 1 (A–I)**: `ALL-OVER-BODY`, `BLEED`, `BREATHE`, `CHOKE`, `COUGH`, `CUT`, `DIZZY`, `FAINT`, `HURRY`, `HURT`, `ITCH`

(4) **Symptoms 2 (P–Z)**: `PAIN`, `PASS-OUT`, `SWEAT`, `STAB`, `STITCH`, `VOMIT`

(5) **Substance Related**: `ALCOHOL`, `COCAINE`, `DRUG`, `MARIJUANA`, `PILL`, `TAKE-PILL`

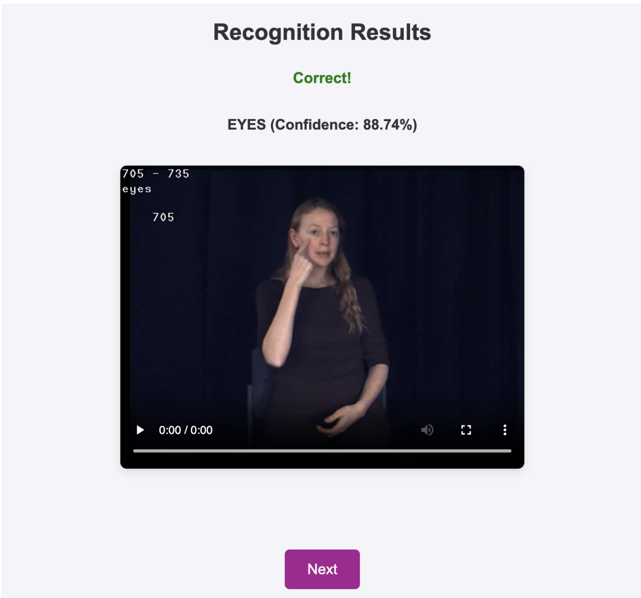
(6) **Medical Terms (A–P)**: `BANDAGE`, `BANDAID (Version 1)`, `BANDAID (Version 2)`, `DOCTOR (Version 1)`, `DOCTOR (Version 2)`, `HOSPITAL (Version 1)`, `HOSPITAL (Version 2)`, `MEDICINE`, `NURSE`, `PATIENT (Version 1)`, `PATIENT (Version 2)`, `PATIENT (Version 3)`, `PHARMACIST`

(7) **Medical Terms (S–W)**: `STETHOSCOPE (Version 1)`, `STETHOSCOPE (Version 2)`, `STETHOSCOPE (Version 3)`, `STETHOSCOPE (Version 4)`, `SURGERY`, `THERMOMETER`, `WHEELCHAIR`

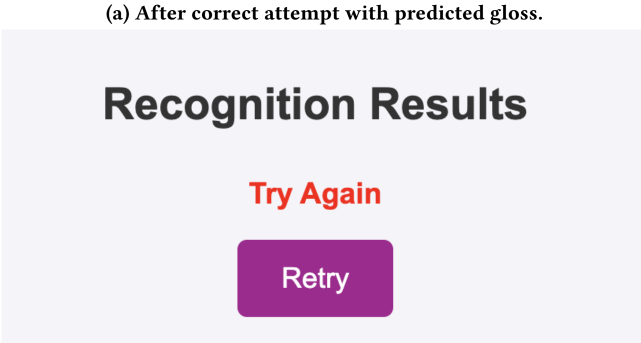
(8) **Injuries**: `ACCIDENT`, `BURN`, `NOSEBLEED`, `STAB`, `CUT`

(9) **Emergencies and Others**: `ALARM`, `ALRIGHT`, `ARREST (Version 1)`, `ARREST (Version 2)`, `ARREST (Version 3)`, `COLLAPSE`, `DEATH`, `DIE`, `EARTHQUAKE`, `HURRICANE`, `RESCUE`

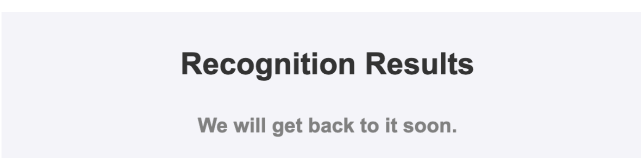
B Feedback Interface



(a) After correct attempt with predicted gloss.



(b) After first incorrect attempt with 'Retry' button.



(c) After second incorrect attempt with deferred sign.

Figure 2: Recognition feedback: (a) Correct attempt, (b) First incorrect attempt, (c) Second incorrect attempt.